A GAUSSIAN PROCESS BASED DATA MODELLING AND FUSION METHOD FOR MULTISENSOR COORDINATE MEASURING MACHINES

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INTRODUCTION

Multisensor measurement technology is an emerging technology which makes use of combinations of two or more different types of sensor probes so as to further enhance the measurement capability of the traditional single sensor coordinate measurement machines (CMMs). The sensors can complement each other's limitations and improve the measurement accuracy. Nowadays, the applications of multisensor CMMs are becoming more and more widespread and many CMM manufacturers are developing multisensor CMMs in their advanced production lines. For instances, ZEISS O-INSPECT [1] equips with a contact sensor, imaging sensor and white light distance sensor, which is able to provide a fast inspection by the image sensor and high accuracy 3D measurement results by the contact sensor and white light distance sensor. Werth VideoCheck [2], is designed to equip with many kinds of sensors such as trigger probe, fiber probe and video sensor which provides the measurement ability of small features with the help of the small-diameter fiber probe in the scale down to 20 µm, as well as a quick checking with the fast trigger probe and image sensor. Hexagon Optiv Classic [3] provides a vision sensor and a tough trigger probe, while Nikon [4] enhances the true 3D multi-sensor measurement by combining vision sensor, laser auto-focus sensor, tactile sensor and rotary indexer. The measurement range, resolution and flexibility are largely enhanced by the complementary of the different characteristics of various sensors.

The combination of different types of sensors extends the measurement ability such as accuracy and measurement range of the CMMs. However, most of the multisensor CMMs are lack of an optimal strategy to perform multisensor measurement and fusion of data from different sensors. Some of the studies for multisensor CMM focused on complementary measurement for special geometrical features. Nashman et al. [5] used a camera sensor to locate and measure the feature such as object edges, corners and centroids while the touch sensor was used to measure other part of the object. The touch sensor was highly accurate with little noise. However, it could not measure sharp features such as edges and corners. Combining these two sensors enable the capability to gather high bandwidth global information and to obtain high accurate measurement information. Zexiao et al. [6] used a multi-probe system which consists of a structure light sensor and a trigger probe to measure multiple features including edges. However, the edges were not directly measured while they were generated by fitting the surfaces using the measured points on the relatively smooth surfaces instead.

This paper presents a Gaussian process based data modelling and data fusion (GP-DMF) method which first estimates the mean surfaces and uncertainties of the datasets obtained from different sensors and combines the two measurement data into a single one with associated uncertainty. A series of simulation and measurement experiments have been conducted to verify the technical feasibility of the method. The results show that the fused data with a lower uncertainty are obtained. The proposed GP-DMF method attempts to provide a generalized data-orientation multi-sensor measurement method which does not rely on the sensor itself and this makes it having potential to be used in a wide application fields.

GAUSSIAN PROCESS BASED DATA MODELLING AND FUSION METHOD

The proposed data modelling and fusion method is shown in FIG. 1. The measurement datasets from different sensors are firstly modelled with Gaussian Process (GP) modelling. Hence, the mean surfaces and their associated uncertainties are determined. The mean surfaces are registered into a common coordinate system with the iterative closest point (ICP) method. As a result, the two datasets are fused together using the maximum likelihood method.

The measurement process can be considered as a Gaussian process (GP) which is a stochastic process with a mean function *m* and a covariance function *k*, and it can be expressed as Eq. (1) [7].

$$f \sim GP(m,k) \tag{1}$$

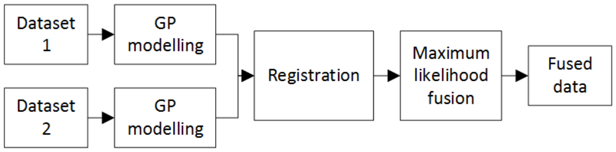


FIGURE 1. Diagram of the data modelling and maximum likelihood data fusion method

In the present study, the Gaussian process modelling is undertaken by using the Gaussian processes for machine learning (GPML) toolbox [8]. The mean function is chosen to be zero mean since the underlying surface is supposed to be unknown and the covariance function is chosen to be squared exponential function since the measured surface is targeted to be continuous freeform surface.

Although the coordinate information of the sensors equipped with the multisensor CMMs can be calibrated with a standard artifact [9], there is still residual error for the relative position for the sensors. The registration process aims to minimize the residual error and the ICP [10] method is used in this study.

The mean surface and the associated uncertainty are then fused together with a Bayesian inference based maximum likelihood method. For two measurement data z_{m1} and z_{m2}, which can be determined by

$$z_{m1} = z_1 \pm \sigma_1 \quad (2)$$

$$z_{m2} = z_2 \pm \sigma_2 \quad (3)$$

where z_1 and z_2 are the measurement results and σ_1 and σ_2 are the associated uncertainties. The sensor models are given by the Gaussian likelihood function as shown below:

$$p(x \mid z_1, \sigma_1^2) = \frac{1}{\sigma_1\sqrt{2\pi}} \exp\left(-\frac{(x-z_1)^2}{2\sigma_1^2}\right)$$
$$p(x \mid z_2, \sigma_2^2) = \frac{1}{\sigma_2\sqrt{2\pi}} \exp\left(-\frac{(x-z_2)^2}{2\sigma_2^2}\right) \quad (4)$$

Hence,

$$p(x \mid z_1, \sigma_1^2, z_2, \sigma_2^2) = p(x \mid z_1, \sigma_1^2)\, p(x \mid z_2, \sigma_2^2)$$
$$= \frac{1}{2\pi\sigma_1\sigma_2} \exp\left(-\frac{(x-z_1)^2}{2\sigma_1^2} - \frac{(x-z_2)^2}{2\sigma_2^2}\right) \quad (5)$$

The log of above function is:

$$L(x \mid z_1, \sigma_1^2, z_2, \sigma_2^2) = C_1 - \left(\frac{(x-z_1)^2}{2\sigma_1^2} + \frac{(x-z_2)^2}{2\sigma_2^2}\right) \quad (6)$$

From Bayes' theorem, the fused best estimate is given by

$$\hat{z} = \arg\max[L(x \mid z_1, \sigma_1^2, z_2, \sigma_2^2)] \quad (7)$$

Hence, $\frac{\partial L}{\partial x} = 0$

The fused result can be derived by Eq. (8) while Eq. (9) shows the standard deviation which represents the fused uncertainty.

$$\hat{z} = \left(\frac{z_1}{\sigma_1^2} + \frac{z_2}{\sigma_2^2}\right) / \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}\right) \quad (8)$$

$$\hat{\sigma} = 1 \Big/ \sqrt{\left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}\right)} \quad (9)$$

Eq. (8) and Eq. (9) show that the fused data represent the overall best estimated measurement result with a lower uncertainty than both original data. The fusion of the two measurement data is illustrated in Fig. 2. Eq. (8) and Eq. (9) also show that when one measurement is more accurate than another one, the weighting for the more accurate one is much larger than the other one in a quadratic relation. When the measurement uncertainty for the less accurate sensor is more than three times of the accurate one, the influence of the less accurate one is insignificant for the overall result.

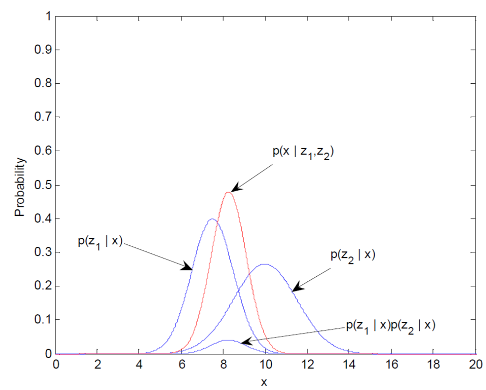


FIGURE 2. Fusion of two Gaussian distributions [11]

EXPERIMENT VERIFICATION WITH SIMULATED SURFACES

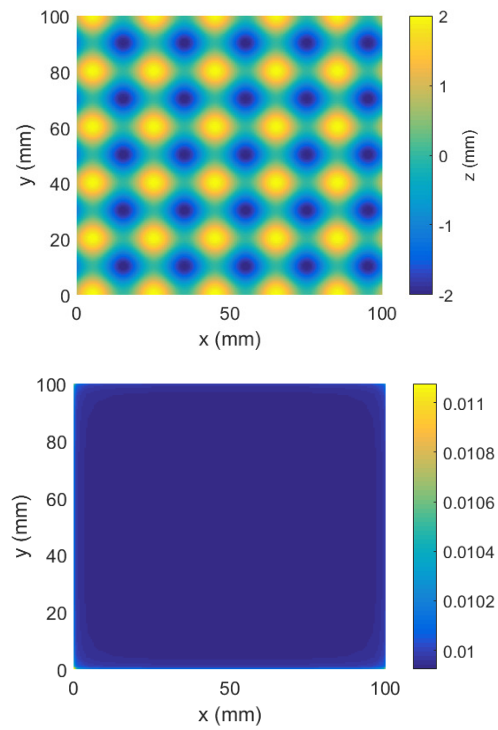
Two simulated sinusoidal surfaces with different levels of measurement noises are designed which are determined by Eq. (10).

$$z = \sin(\frac{\pi}{10}x) + \cos(\frac{\pi}{10}y) + N_m \quad (10)$$

where N_m is the measurement noise, for data set 1, $N_m = 0.01$ mm, for data set 2, $N_m = 0.005$ mm.

FIG. 3 and FIG. 4 show the mean surfaces and the estimated uncertainties of the data set 1 and data set 2 after Gaussian Processing modelling. The result shows that the simulated measurement noise is well modelled by the Gaussian Process in the covariance.

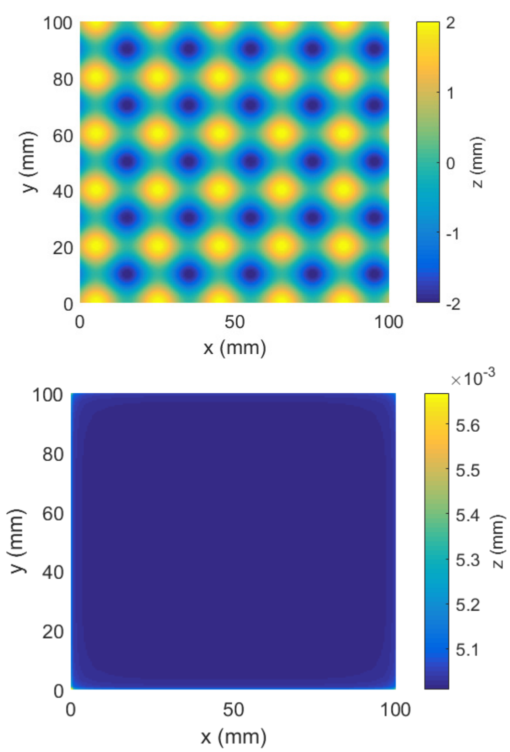
After the Gaussian Process data modelling, the two datasets are then fused with the maximum likelihood method and the result is shown in FIG. 5. The result shows that the fused uncertainty value is smaller than both original measurement data. The uncertainty for dataset 1 is 10 µm while the uncertainty for dataset 2 is 5 µm, which is much smaller than dataset 1. The fused data is 4.5 µm which only shows small improvement than the dataset 2. The deviation from fused mean surface to design surface is shown in FIG. 6 and the result shows that the deviation is well covered by the uncertainty coverage in the fused data.



(a)

(b)

FIGURE 3. Mean and uncertainty of dataset 1



(a)

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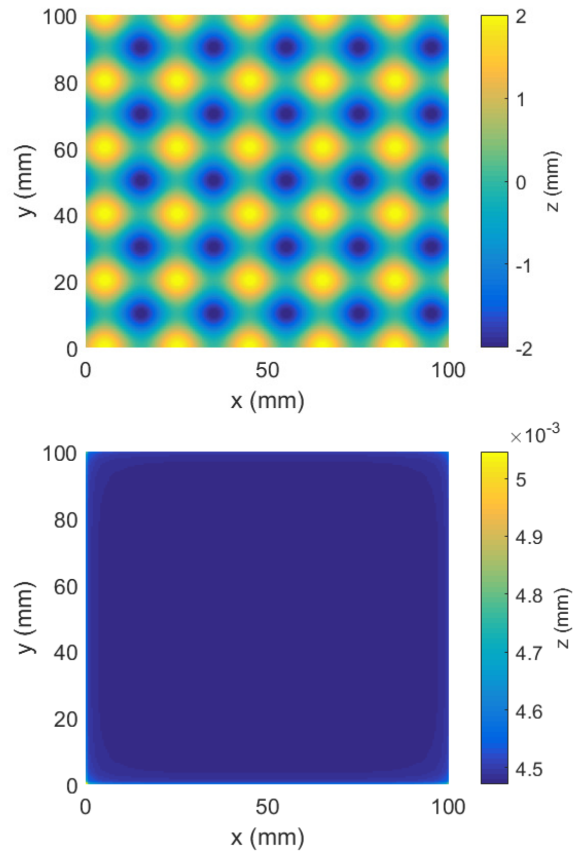
FIGURE 4. Mean and uncertainty of dataset 2



(a)

(b)

FIGURE 5. Fused mean surface and uncertainty.

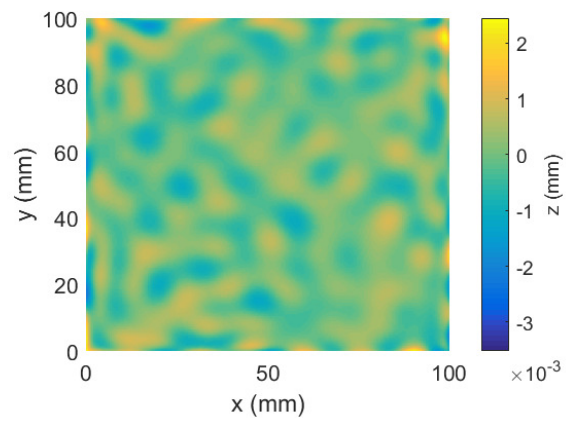


FIGURE 6. Deviation from fused mean surface to design surface.

EXPERIMENTAL VERIFICATION WITH A MULTISENSOR CMM MACHINE

To verify the proposed GP-DMF method, a series measurement experiments were conducted on a Werth multisensor CMM machine. A workpiece was designed, machined, measured and followed by the data processing procedure. The workpiece was designed to be a sinusoidal surface and it was machined by a CNC machine. The machine surface was measured by a laser sensor and a trigger probe. FIG. 7 shows the measurement process using the laser sensor of the CMM machine.

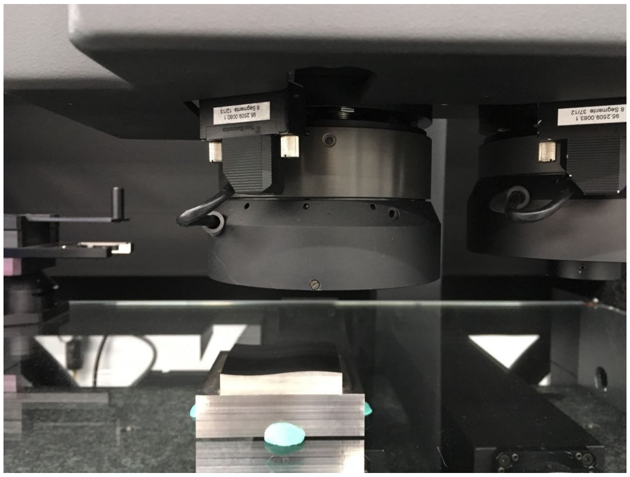


FIGURE 7. Measurement process using the laser sensor

The measurement starts with the laser sensor and a series sampling points were obtained as shown in FIG. 8.

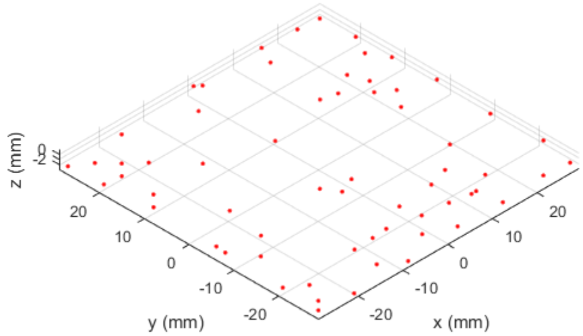


FIGURE 8. Sampling points using laser sensor

The mean surface and the estimated measurement uncertainty for the measured dataset using Gaussian process are shown in FIG. 9. It is interesting to note that the measurement uncertainty for the laser sensor is quite large (from 26 to 32 µm) which may be caused by the surface characteristics such as reflection.

A CAD model was generated as shown in FIG. 10 by using the mean surface of the laser scanned data so as to guide the measurement of the trigger probe. The sampling data using the trigger probe is shown in FIG. 11.The mean surface and the estimated uncertainty for the measurement data of the trigger probe after Gaussian process are shown in FIG. 12. The results show that the uncertainty range is about 6-8 µm which is much smaller than that from the laser sensor. FIG. 13 shows the mean surface and uncertainty after data fusion, and it shows that there is only a small amount of improvement in the fused uncertainty..

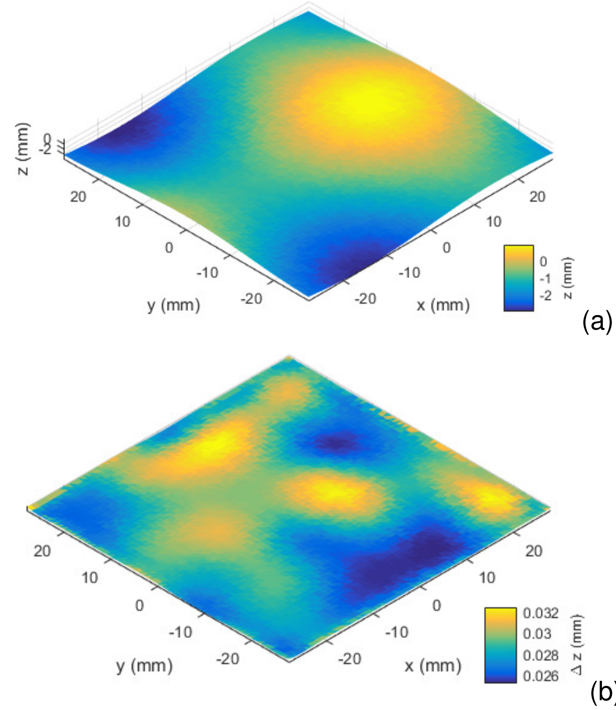


FIGURE 9. Mean surface and estimated uncertainty for the measured data from laser sensor

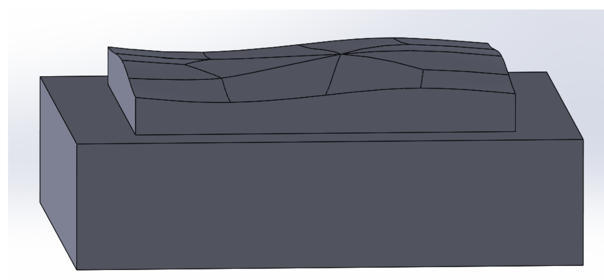


FIGURE 10. CAD model generated from the mean surface of the measured data of the laser senor

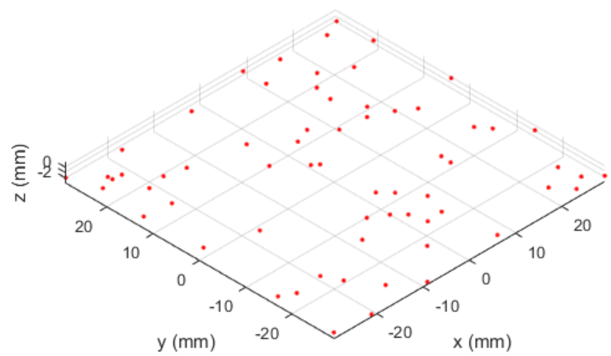


FIGURE 11. Sampling points using trigger probe

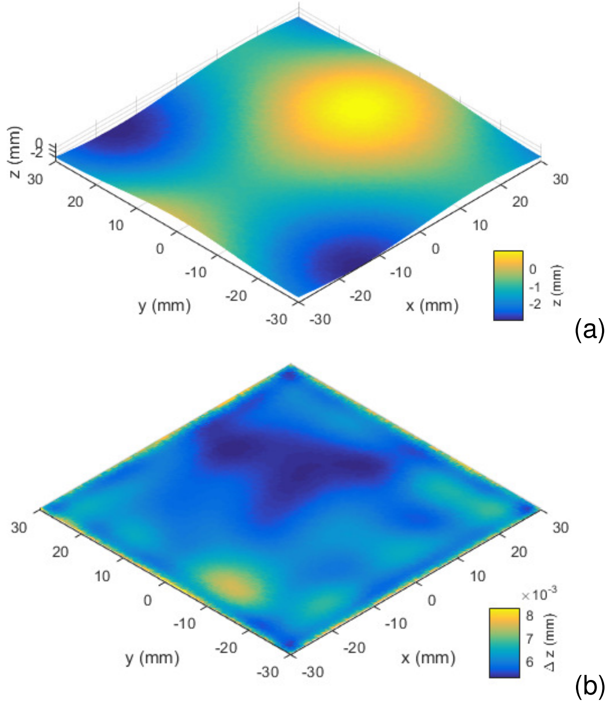


FIGURE 12. Mean surface and estimated uncertainty for the data from trigger probe

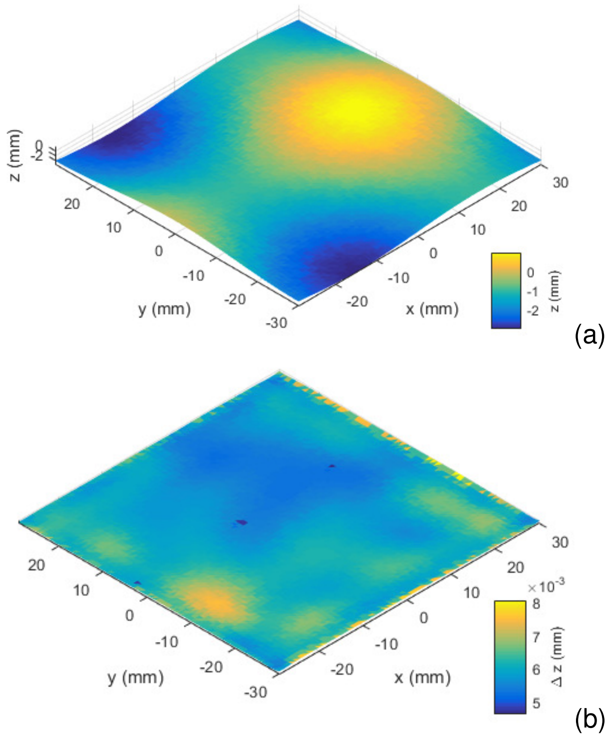


FIGURE 13. Fused mean surface and estimated uncertainty

CONCLUSION

This paper presents a Gaussian process based data modelling and fusion (GP-DMF) method and the effectiveness of the method is verified in a simulation and real measurement experiment. The result shows that the fused result has a lower measurement uncertainty. The proposed method is technically feasibility to be used to enhance the measurement ability for multisensor CMMs.

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