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A study of a priori knowledge-assisted multi-scopic metrology for freeform surface measurement

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Abstract

The traditional multi-scopic metrology system makes use of a micro lens array to capture a raw 3D-image of the target surface in a single snapshot through a CCD camera under normal illumination. However, the resolution of the system depends on the matching precision and efficiency of disparity information during the processing of the 3D raw data. In this paper, the a priori knowledge-assisted multi-scopic metrology is studied and an a priori knowledge-assisted multi-scopic metrology system is established which makes use of patterned illumination custom-designed based on the a priori knowledge of the target freeform surface profile. The a priori knowledge provides abundant versatile known information for a precise and efficient matching process so as to enhance the measuring performance. A customized disparity matching process based on the a priori knowledge is developed accordingly for high-resolution 3D surface reconstruction. An experimental study for measuring freeform surface is conducted to verify the feasibility of the proposed a priori knowledge-assisted multi-scopic metrology system through the comparison between that using normal illumination and a priori knowledge-assisted patterned illumination.

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Keywords: Precision surface measurement, freeform surface, a priori knowledge-assisted, multi-scopic metrology, autostereoscopy

1. Introduction

Freeform surfaces have been widely used in recent decades due to the peculiarity of tolerating special designs which can realize various optical and mechanical functions [1]. Geometrical accuracy of the surface is of great importance to the functional performance. However, freeform surfaces are more complex. which impose huge challenges to the measuring process, which can directly influence the manufacturing process control and final product quality. Various technologies have been developed and widely used in precision metrology including coordinate measurement machine (CMM) with the use of a contact probe or non-contact optical probe, optical-based light scattering techniques [2], fibre interferometry [3] and optical slope sensors [4]. Multi-scopic 3D technology can provide multi-perspectives of the same scene as the raw 3D information for 3D digital reconstruction. It is a new terminology with a precise definition of a technology previously known as a kind of autostereoscopic-based measurement method and system for the measurement of micro-structured surfaces [5]. The multi-scopic 3D technology makes use of a compact system design to acquire 3D raw data within a single snapshot. It provides a competitive advantage as on-machine measurement incorporated in on ultra-precision machine tool. This is particularly true when the measuring environment needs to be vibration-tolerant in order to preserve the measuring accuracy. When faced with a surface profile consisting of large dynamic ranges, the measuring performance needs to be enhanced, especially in terms of resolution.

There is a close relation between causing a low relative resolution and the matching process of the 3D raw data processing method of the multi-scopic 3D measuring technology. As a machine vision-based measurement method which uses pixel information as the main medium during data processing, the diversity of the pixel information distribution (PID) determines the resolution of the matching process. The

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diversity of PID means that the certain regional pixel information has a large range of pixel values. The reason for the determination between diversity and resolution is that the diversity of PID has a direct relation with the feature of the PID and this feature can directly determine the matching process of the pixel information. PID with low diversity can cause low matching accuracy and low matching efficiency which directly leads to low measuring accuracy. Meanwhile, other features of the surface profile which lead to homogeneous PID, such as higher slope angles, continuous surface profile, lower roughness or special structure which cause multiple internal reflection under normal illumination, results in a poor matching process and low measuring accuracy.

As a result, this paper presents an a priori knowledge-assisted multi-scopic metrology system to overcome the deficiencies as analyzed above. Experimental studies using the proposed a priori knowledge-assisted multi-scopic metrology system to measure the mould of a lamp shield of spot light verify the feasibility of the proposed method and compare the performance of different patterned illumination towards the normal illumination.

2. A Priori knowledge-assisted metrology method

The multi-scopic 3D measurement method is a novel theory which has been proposed recently [5]. The associated metrology system has a concise system setup which consists of a main lens, a CCD camera and a micro lens array (MLA). It can capture the raw 3D information of the target surface within a single snapshot. The 3D digital model of the target surface can be precisely reconstructed through a system-associated 3D raw data processing method.

2.1. Basic principle

Fig. 1 shows the basic principle of the a priori knowledge-assisted multi-scopic metrology system step by step. Basically, it is divided into two processes including recording process and reconstruction process. As the key component in this system, the MLA can capture elemental images (EIs) with slight differences since the spatial locations of elemental lenses of MLA are different. This is discovered in the EIs shown in the upper right of Fig. 1. These differences between elemental images are called disparities. These image points from different elemental images which originate from an identical single object point in the object space are called corresponding points (CPs) [6]. Disparities can store the 3D information of the target which is transferred to the reconstruction process to build the 3D digital model. Disparity is the key parameter that has a quantitative relationship with the depth and lateral coordinates with the aid of other parameters of the system setup. As a machine vision-based method, the disparity information can be represented by the number of pixels and single pixel size which are calibrated with dimensions from the real 3D world.

Fig. 1 shows the five steps from the capture of raw 3D information of the target to the reconstruction of 3D information of the target. It selects a set of three sample points for simple illustration which have different spatial locations in both the lateral and depth directions from a freeform surface. The sample points are marked as a circle (red), square (blue) and cross (green) as shown in Fig. 1. As the 1st step, these three points are obviously recorded with different relative distances in different elemental images according to the above analysis.

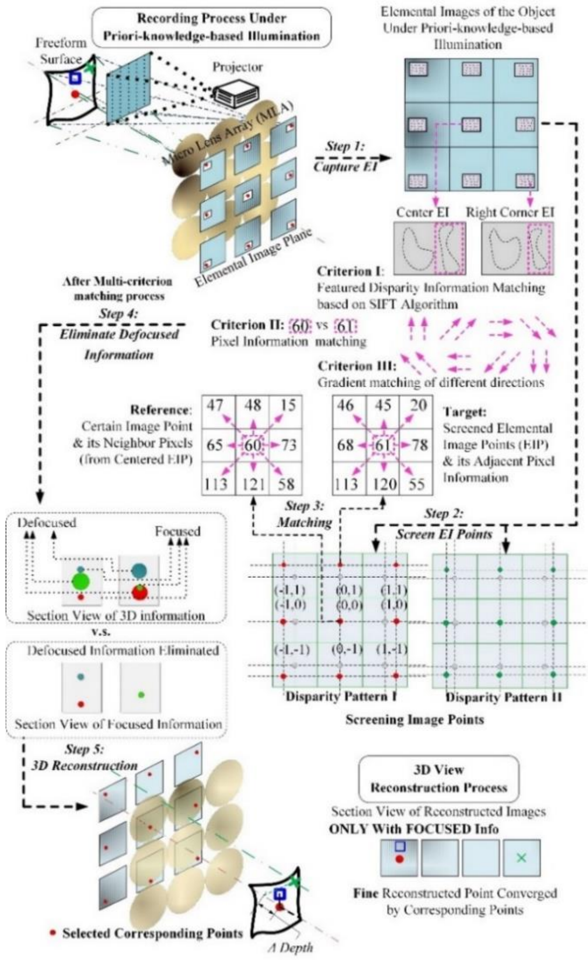

Fig. 1. Basic principle of the a priori knowledge-assisted multi-scopic 3D measurement method

Based on knowledge of geometrical optics, the sample points from the same depth plane have identical disparities. However, the overall positions of a set of CPs have lateral translations compared with other sets of CPs which come from the same depth plane. Meanwhile, for the sample points from different depth planes, there is a quantitative relationship of great importance between the between the depth and disparity value. The quantitative relationship can determine the disparity value and screen the image points from EIs. This is the 2nd step of the whole process. These CPs can be extracted from the elemental images group by group and named a disparity pattern as shown in Fig. 1, the disparity pattern I originates from the solid (red) sample point and disparity pattern II originates from the cross (green) sample point. It is easy to discover that these two patterns have different relative distances between CPs which are the different disparities. This is because they originate from different depths. As the 3rd step, the set of screened image points from elemental images which are in accordance with the disparity pattern can be finally determined as the CPs through the matching process. This multi-criterion-based matching process is elaborated in section 2.2.

After step 3, the EI points that pass the matching process converge into a fine-focused image point through the MLA at its corresponding depth plane based on the symmetrical relationship between the recording process and reconstruction process. In Fig. 1, it is easy to discover that the schematic draws of recording process from the top part and reconstruction process from the bottom part are symmetrical, which means that the 3D information of the object space can be identically restored during the reconstruction process on the premise of having the same MLA and other systematical parameters. The defocused image point which does not belong to its corresponding depth plane can be eliminated during the matching process of screened EI points which is also shown in Fig. 1. as the 4th step. Since the pixel size is a known factor, the quantitative relationship between disparity and depth and lateral distance can be constructed through the counting of pixel size. The clear and focused image points at different depths can construct the whole 3D digital model of the targeted surface. This is the 5th step of the whole process from the capture to the reconstruction of the 3D information.

2.2. Multi-criterion-based data processing method

After the extraction of the disparity pattern based on the theoretical quantitative relationship of the multi-scopic 3D measurement method, an additional process needs to be operated to finally determine whether the screened image points from the disparity pattern are CPs or not. The traditional method uses the absolute pixel value and gradient between screened image points to realize the evaluation of CPs [7]. However, this method does not perform well when there is a plain PID in the elemental images since there is limited difference between pixels and it is hard to set up thresholds for the differences to precisely eliminate false CPs.

With the assistance of patterned illumination, which is designed based on the a priori knowledge, the PID in the elemental images varies a lot and provides features for the information matching process. The functionality of a priori knowledge-based illumination is also specifically shown in Fig. 1. Three criteria based on the PID are mainly applied to the 3D raw data process after the image points are screened based on the disparity pattern, featured disparity information matching, pixel information matching and gradient matching of different directions. A multi-criterion-based data processing method is developed and illustrated in Fig. 1.

The a priori knowledge-assisted patterned illumination provides great peculiarity to the PID which can be adopted as criteria to perform matching and elimination operation. Different matching criteria calculated through the a priori information are used to construct the final disparity map. Featured details originating from the patterned light illumination which is captured by the multi-scopic 3D metrology system as the 3D raw data are processed by scale-invariant feature transform (SIFT) [8] to become the matching criterion for the disparity information extraction. Moreover, the absolute difference (ABD) and the gradient difference (GRD) of various directions between the to-be-determined point and the referenced point are also used as criteria to finalize the disparity map. The matching process in Fig. 1 is used for brief illustration. Eq. (1) shows the construction of three different criteria using different coefficients.

$$D_r = \arg\min_{l} \sum_{x} D(x, l(x)) + \sigma_1 \sum \| l(x) - l_a(x) \| + \sigma_2 \sum \| l(x) - l_{SIFT}(x) \| + \sigma_3 \sum \| l_a(x) - l_{SIFT}(x) \| \qquad (1)$$

In Eq. (1), it has four different parts. The 1st item is the basic difference of disparity information part, and the mathematical description of the expression "$arg\ min \sum_x D(x, l(x))$" aims to find all the variable x to construct the minimum value of the sum of $l(x)$. The 2nd item is the difference between the refined disparity map using the "winner-takes-all" strategy $((l_a(x)))$ and the original disparity map ($l(x)$), the 3rd item is the difference between the initial disparity map ($l(x)$) and the one generated by the SIFT process $(l_{SIFT}(x))$ and the 4th item is the difference between the disparity map after an additional process $(l_a(x))$ and SIFT process $(l_{SIFT}(x))$. σ_1, σ_2 and σ_3 are the parameters to control the weight of these differences. They are empirically set as $\omega_1 = 0.5, \omega_2 = 10, \omega_3 = 1$. The final value of this overall matching process needs to be minimized for full credibility of the matching process. The main components in Eq. (1) is expressed below:

The estimation of the basic disparity information which is the 1st item of Eq. (1) makes use of the following mathematical structure through the criterion of ABD and GRD which is expressed as:

$$D = \alpha D_{ABD} + (1-\alpha) D_{GRD} \qquad (2)$$

where D is the function of difference defined by the reference and target positions, D_{ABD} represents the Absolute Difference (ABD) and D_{GRD} represents the Gradient Difference (GRD). α is the weight parameter and is empirically selected as $\alpha = 0.45$.

In Eq. (2), the ABD can be determined through:

$$D_{ABD}(x,l) = \sum_{s \in V} \sum_{x \in R_x} \min(|I(x+\Delta x) - I(x)|, \omega_1) \qquad (3)$$

where ω_1 is the upper limit to control the quality of the ABD value. It is set to the value of 1 according to multiple trial experiments. The symbol "*min*" aims to select the minimum value within the matching region, while the GRD in Eq. (2) is represented through:

$$D_{GRD}(x,l) = \sum_{s \in V} \sum_{x \in R_x} \gamma_1 \min(Diff_{\rightarrow}, \omega_2) + \gamma_2 \min(Diff_{\rightarrow\downarrow}, \omega_2) + \cdots + \gamma_8 \min(Diff_{\uparrow\rightarrow}, \omega_2) \qquad (4)$$

where ω_2 is the upper limit to control the quality of the GRD value and it is empirically set to $\omega_2 = 3$, and the symbol "*min*" also means to select the minimum value. The parameter γ is the weight of gradient difference of different directions. Currently it is set to have the same weights of all the eight directions.

The whole mathematical process of the proposed multi-criterion-based disparity information extraction is summarized above. Once the minimum value of this parameter is sought, the disparity matching process is evaluated as a success. Based on fundamental theory of multi-scopic 3D measurement method, this confirmed disparity information and the real dimensions has a linear relationship. The final 3D digital model can be reconstructed through this multi-criterion-based disparity information extraction method with the assistance of a priori knowledge of the target surface.

3. A Priori knowledge-based patterned illumination design

Based on the analysis above, the PID of the elemental images needs to vary in order to enhance the matching precision and the accuracy of 3D raw data captured by the multi-scopic 3D measurement method. The improved matching accuracy can directly enhance the system resolution. Using patterned illumination to replace the normal illumination is the most direct way to generate a diverse PID. However, the PID should not conflict with the surface profile, as the poor alignment with the surface profile may cause errors or even wrong detection by this machine vision-based measurement system. The pattern needs to be specifically designed based on the a priori knowledge of the surface profile, such as the design data or the measurement data from other measurement systems.

Design data are selected as the a priori knowledge to design the patterned illumination in this study. Fig. 2 shows different designs of a priori knowledge-assisted patterned illumination and the associated illumination status of the target. The design data of the target surface are shown in Fig. 2(a). The target surface has multiple structures. Three types of patterned illumination are designed including the sinusoidal pattern, linear pattern and simulated-curve pattern, respectively. Fig. 2 also elaborates different designs of the patterned illumination. The sinusoidal pattern makes use of standard sinusoidal distribution to align the designed surface profile. Although the curvatures of structures are different, the top of the designed surface profile is allocated the peak of the standard sinusoidal wave and the highest amplitude, and the bottom of the structure is allocated the valley of the standard sinusoidal wave and the lowest amplitude. For the linear patterned illumination, it has a similar allocation as the top and bottom part of the structure, but the standard sinusoidal wave is replaced with the linear distribution. For the last design using simulated-curve pattern illumination, the light intensity distribution is identical to the design surface profile. They are specific designs of different patterned illumination based on a priori knowledge of the target surface.

The final outputs of the four different patterned light projections and the real structures under these patterned illuminations are also shown in Fig. 2. Since the surface roughness of this designed surface is low and has multiple inner reflections within the structure, the originally-planned PID is re-distributed. Under the illumination of normal light, the overall output PID which is received by the multi-scopic 3D metrology system is plain with less features. On the contrary, different patterned illumination can provide various PIDs with different surface profiles. The inherent inner reflectiveness has limited influence compared with normal light illumination and does not lead to an overall plain PID of elemental images. Moreover, from the comparisons of real target surfaces under different illuminations, it can be vividly discovered that the target with patterned illumination has a steeper visual output than that of normal illumination.

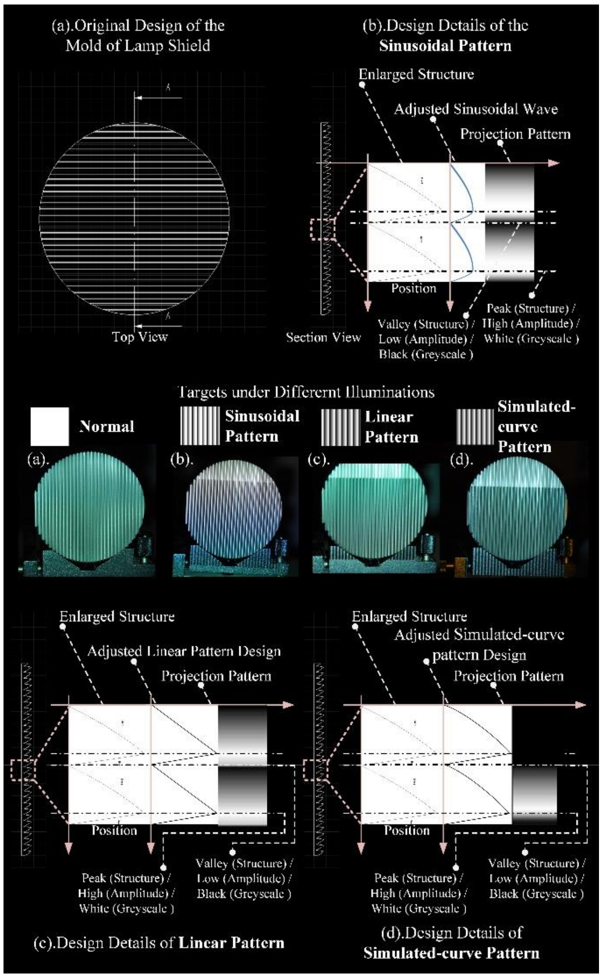

Fig. 2. Different designs of a priori knowledge-assisted patterned illumination and the associated illumination status of the target (a) Normal Illumination; (b) Sinusoidal Pattern Illumination; (c) Linear Pattern Illumination; (d) Simulated-curve Pattern Illumination

The main aim of using a priori knowledge to design patterned illumination and the multi-scopic 3D measurement system is used to generate various PIDs within the single period of the structure for the data acquisition of the proposed system. The range of pixel information needs to be wide enough and versatile enough which is the design idea of the four different patterned illumination. Moreover, the a priori knowledge provides guidance to select the thresholds since the PID of the projection is accessible based on the a priori knowledge. The four designs of patterned illumination radically avoid mismatching during the disparity matching process among different regions of the freeform surfaces.

4. Experimental study

In order to evaluate the feasibility of the proposed a priori knowledge-assisted multi-scopic 3D measurement system and compare the different performance among four a priori knowledge-based patterned illuminations, multiple measuring processes under different illumination statuses was investigated through experimental studies in this research.

4.1. The experimental system setup

The upper Fig. 3 shows the schematic diagram of the a priori knowledge-assisted multi-scopic 3D measurement system, which mainly consists of three modules: the multi-scopic module, the illumination module, and the information generation and processing module. The patterned illumination is customized designed based on the a priori knowledge and generated using Matlab^{TM} software. A projector is adopted in the proposed metrology system in order to introduce patterned illumination to the target surface.

The lower Fig. 3 shows the experimental setup of the proposed a priori knowledge-assisted multi-scopic metrology system. A Lytro Illum light field camera is used in this experimental study to conduct the feasibility test of the proposed method and eliminate other possible influences which are not from the proposed method. A portable projector is incorporated in the proposed system to output the a priori knowledge-based patterned illumination to the target surface. A three-translational stage is used to provide precise adjustments and alignments. For the best use of the encoded light information, the environmental light is well controlled.

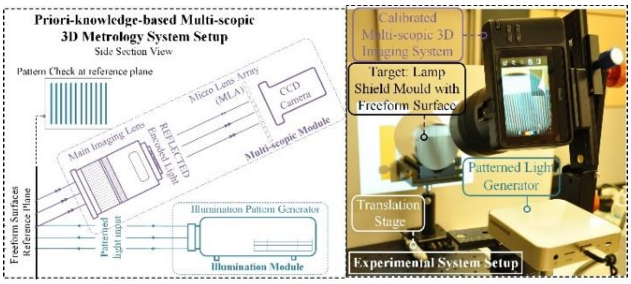

Fig. 3. Schematic drawing and experimental setup of the a priori knowledge-assisted multi-scopic metrology system

In this experimental study, a mould of a lamp shield of spot light is selected as the target surface which is a freeform surface that consists of multiple structures on it. The high slope of the structure and low surface roughness are the two features leading to the homogeneous PID that severely influence the performance of the measuring results.

Meanwhile, the functionality of a priori knowledge-based patterned illumination needs to be guaranteed by strict alignments and calibrations between the patterned information and surface structure. In this experimental study, an additional vision-based calibration tool using a microscopic object lens is adopted to monitor the status and ensure the consistency of the relative position and consistency between the knowledge-based projected pattern and structure with the aid of the high-precision 2D translation stage. After the calibration of the patterned illumination, the scale between the pixel size and real dimensions needs to be calibrated independently through the artefact with known dimensions. The artefact needs to be measured by the proposed system. After this process, the link between known dimensions of the artefacts and measured scaled data of the artefacts is determined.

4.2. Experimental result analysis

In order to show the advantages of the proposed a priori knowledge-assisted 3D multi-scopic metrology system and its associated multi-criterion-based disparity match algorithm, the target surface is captured through the proposed system under different illumination for 3D raw data acquisition multiple times in order to eliminate system error after the calibration process of the patterned illumination and scale. Fig. 4 shows the experimental 3D reconstruction results of target different illumination, including normal illumination which is white light, sinusoidal wave-patterned illumination, linear-patterned illumination and simulated curve-patterned illumination which are shown in Fig. 4(a) to 4(d). It is found that the structures of the target surface are merely detected under normal light illumination. As shown in Fig. 4(b) to 4(d), the 3D digital reconstruction of the target surface with better detections and restoration of 3D information are vividly shown. The obvious differences between the two categories of results can substantiate the feasibility, the advantages, and its associated data processing of the proposed metrology system.

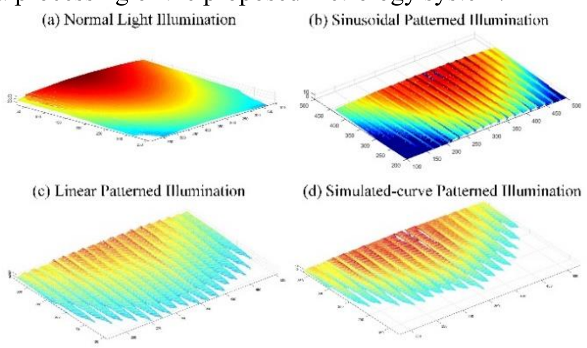

Fig. 4. Comparisons of 3D digital reconstruction of the target under different illumination styles. (a) Normal Illumination; (b) Sinusoidal Pattern Illumination; (c). Linear Pattern Illumination; (d). Simulated-curve Pattern Illumination

The reason why the target surface is not detected well under normal illumination is because the homogeneous PID caused by normal white light illumination is also discovered as the 2D image of the real target under normal illumination as shown in Fig. 2. A priori knowledge-assisted patterned illumination provides a diverse PID with more features. The multi-criterion-based disparity matching algorithm allows the features of the surface profile to be detected along with the features of the illumination provided by the a priori knowledge-based patterned illumination.

Moreover, the performance of different a priori knowledge-based patterned illumination also exhibits differences during the detection and reconstruction of the target surface. This is because the design of the surface profile and the low surface roughness can lead to multiple inner reflections within the single structure. In this sense, the PID also changes slightly compared with the original design of light intensity distribution. Among the three methods, the sinusoidal pattern, linear pattern and simulated-curve pattern, the sinusoidal pattern can cause plainer distribution compared with the other two methods because the sinusoidal wave has a steeper increase from the bottom part to the top part, which is demonstrated specifically in Fig. 2(b). Part of the PID whose location is near to the top part can be reflected to the opposite part and severely jeopardize the original PID.

After the scale transfer based on the calibration process of the proposed system, the error analysis of the measuring results can be achieved through surface registration with another credible off-line measurement system, the Alicona non-contact 3D metrology system. An Iterative Closest Point (ICP) is used to perform surface registration and the result is shown in Fig. 5 with the root mean square error (RMSE) calculation results. The RMSE is calculated through Eq. (5).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_p - x_r)^2}{n}} \tag{5}$$

where n is the total number of sample points, x_p is the point cloud data measured from the proposed metrology system, while x_r is the point cloud data measured from reference off-line metrology system, which is also known as the Alicona 3D metrology system in this experimental study.

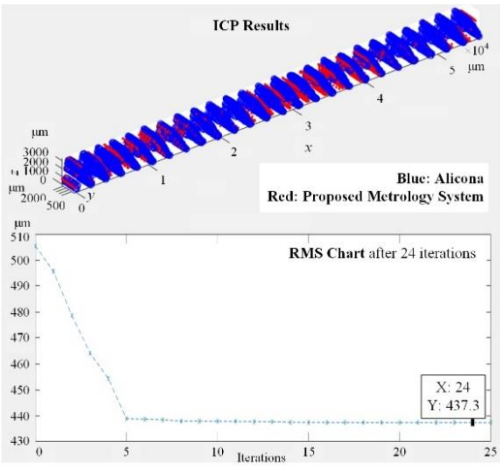

Fig. 5. Surface registration results using the ICP method and RMS results

The proposed a priori knowledge-assisted multi-scopic metrology system can provide measurement results with the RMSE of around 400 μm. Compared with the approximate field of view (FOV) of 80 mm×80 mm, it indicates that the relative resolution of the proposed a priori knowledge-assisted multi-scopic 3D metrology system is around 1/200. The 3D reconstruction result using normal light illumination does not show enough 3D features of the target, which can be discovered in Fig. 4(a). The ICP method fails to perform surface registration with the reference measuring data from the Alicona system. The approximate RMSE is over 3 mm based on the multiple comparisons from measured point data to reference point data.

5. Conclusion and future work

As the conclusion of this research study, the proposed a priori knowledge-assisted multi-scopic 3D metrology system is feasible to be a competent metrology system for the measurement of freeform surfaces with satisfactory precision and repeatability. Moreover, it has potentials to be used to perform on-machine measurements due to its compact system setup and fast data acquisition which can have wider use in the field of ultra-precision machining technologies. Although the current measurement data processing time limits the overall measuring time due to the heavy computation, further work will be done on the use of the Graphics Processing Unit (GPU) acceleration to reduce the data processing time which makes the a priori knowledge-assisted multi-scopic metrology system to be able to perform on-machine measurement with ultra-precision machine tools.

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