Flexible Registration: A higher-precision point cloud registration method applied to multiple sensor group

Changshuai Fang [1], Zhengwen Li [1], and Xiaodong Zhang[1, #]
1 State Key Laboratory of Precision Measuring Technology & Instruments, Laboratory of Micronano Manufacturing Technology, Tianjin University, Tianjin 300072, China
Corresponding Author / Email: Zhangxd@tju.edu.cn

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Multiple sensors registration technology is widely used in applications such as autonomous driving, robotics, and remote sensing. Research has shown that there is still room for improvement in the accuracy of the measurement point cloud obtained from rigid registration. Currently, research can be divided into two aspects. On one hand, data fusion is used to improve the accuracy of partial point clouds, but this method can only be used to repair overlapping areas of point clouds. On the other hand, high-precision feature calculation in multiple dimensions is used to improve registration accuracy or compensate for registration, but the overall accuracy of this method is generally not high. In order to address the problem of high-precision registration in multiple sensors, this paper proposes the concept of flexible registration, which deforms the point cloud by adjusting the sub-sensor model to achieve the highest accuracy of the combined point cloud after registration. This is a new approach to multiple sensors registration. In order to verify the effectiveness of the registration, the multi-line laser vision sensor group is used as the experimental carrier. In order to avoid interference from other factors, various error sources of the sub-sensors are corrected in this paper. On this basis, the measurement accuracy after rigid registration and flexible registration is compared respectively. The experiments show that flexible registration makes the surface shape error of the sensor group more continuous and improves the measurement accuracy. Taking cylinder diameter measurement as an example, the system's measurement accuracy has improved by 80% through flexible registration compared to rigid registration, demonstrating the effectiveness of flexible registration.

NOMENCLATURE

(u, v) are pixel coordinates captured

$P_w(x_w, y_w, z_w)$ is coordinate under displacement table coordinate system

$f(\cdot)$ and $g(\cdot)$ represent the mapping relationship between pixel coordinates and sensor coordinates y and z

RT is the transformation relationship between the sensor coordinate system and the displacement stage coordinate system

RT_{j_2} represents the rotation and translation matrix from the j-th sensor to the 2-th sensor

$[X_{ci} \quad Y_{cij} \quad Z_{cij}]^T$ represents the i-th set of ball center positions of the jth sensor

$[X_{ci2} \quad Y_{ci2} \quad Z_{ci2}]^T$ represents the i-th set of ball center positions of the 2-th sensor

1. Introduction

To achieve a complete observation of an object, there are generally two forms: one uses a single sensor with multiple viewpoints, but sometimes another approach of Multiple sensor group is adopted to improve efficiency. However, Multiple sensor group relies on the registration of coordinate systems, and the accuracy of coordinate system registration directly affects the accuracy of the integrated measurement process, making it an important aspect of the measurement process.

Coordinate system registration in multiple sensors is usually accomplished through rigid registration using common features. For example, [1] used multiple differently sized spheres to calibrate the coordinate system relationships between four laser line scanning sensors. [2] achieved coordinate registration of a dual telecentric imaging system through a micro chessboard, enabling monitoring of the crystal length and width distribution in the cooling crystallization process of a β-LGA. However, [3] mentioned that manufacturing limitations and the accuracy of calibration targets and cameras, as well as potential calculation errors in calibration marker detection algorithms, make it difficult to achieve high-precision point cloud registration using only traditional rigid registration strategies. To achieve high-precision data registration, there are two main research approaches: One way is to adjust the data sources through data fusion. For example, [4] developed a human skeletal tracking system using a Kalman filter framework, where multiple Kinect sensors were used to correct inaccurate tracking data from a single Kinect sensor. Considering the powerful nonlinear mapping ability of deep learning networks, they are also suitable for multi-sensor point cloud fusion, and researchers have conducted relevant studies based on this. [5] proposed the PANet network, which adaptively fuses multi-scale features extracted from multiple branches to enhance the representation capability of point cloud features and improve registration accuracy. However, the aforementioned research primarily focuses on deforming and fusing data in the overlapping regions of multiple sensors, although it improves the accuracy of some point clouds, it fails to improve the accuracy of a large amount of non-overlapping data. Another approach is to adjust the transformation relationships and mainly consists of two methods. One method is to create multi-dimensional, high-precision feature points. For example, [6] proposed a multi-dimensional feature-based point cloud registration algorithm that utilizes interval segmentation. The other method is to nonlinearly correct the registration relationship based on the closed-loop relationship of the measurement system. Considering that the accumulated registration accuracy between sensor coordinate systems is influenced by the precision of target manufacturing and sensor measurement errors, and becomes increasingly significant with the increasing number of sensors. The authors corrected the registration problem caused by error sources by using the weighted linear combination of bidirectional transfer registration matrices and achieved certain results. Although these methods of correcting registration relationships can make reasonable adjustments to all data compared to local data deformations, the improvement in registration accuracy is limited.

The passage presents a flexible registration approach, which involves continuously optimizing the parameters of sensors during rigid registration to achieve the highest measurement accuracy after registration. Different from the commonly mentioned scale invariance principle in previous rigid registration studies, in flexible registration, sensor parameters change to reasonably deform the data of sub-sensors, ultimately leading to more continuous and accurate integrated data. As far as we know, no one has improved the accuracy of point cloud registration by controlling the sub-sensor model. The advantage of this method is that it can improve the accuracy of all data points after registration compared to fusion methods. Compared to the method of adjusting rotation-translation matrix, the registration accuracy can be further improved because the error of the data source used for registration is reduced by modifying the model. In order to demonstrate the effectiveness of flexible registration, this paper constructs a multi-sensor group. Line structured light measurement is a fast and high-precision three-dimensional reconstruction method. However, when measuring the complete contour of axial parts, multiple sets of equipment are often required to achieve full coverage. Therefore, this paper takes this system as a carrier to demonstrate the effectiveness of flexible registration. In addition, in order to avoid interference from other factors, before flexible registration, this paper first corrects the high-precision error sources for each sub-sensor. On this basis, the effectiveness and mechanism of flexible registration compared with rigid registration are explored. Of course, the flexible registration idea proposed in this paper is not limited to line structured light scanning or the field of industrial parts measurement. It can be applied to any field that involves point cloud registration, such as autonomous driving, SLAM, etc.

2. Method

2.1 Measurement principle

In order to fully verify the value of flexible registration, this article needs to achieve high-precision calibration for sub-sensors. Because sensors with high-precision calibration are more likely to be perceived as being able to achieve high-precision coordinate system registration using rigid registration. However, if at this time flexible registration still improves the comprehensive measurement effect of a sensor group that has been calibrated with high precision, it will be easier to clarify the mechanism of action and highlight the value of flexible registration methods.

The model of the subsystem can generally refer to that in [7]. However, [8] mentions that compared with physical models, black box calibration has higher accuracy because nonlinear fitting approximation models are better able to approximate real optical systems than simple pinhole models. In order to fully verify the advantages of flexible registration, therefore, the reconstruction model for single-camera line laser measurement system adopts a black box model as shown in formula (1). They are obtained through black box calibration using XY polynomials.

$$\begin{cases} y = f(u,v) \\ z = g(u,v) \\ \begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} = RT \begin{bmatrix} 0 \\ y \\ z \end{bmatrix} + \begin{bmatrix} x_w \\ 0 \\ 0 \end{bmatrix} \end{cases} \tag{1}$$

The point cloud data of the four sensors can be integrated to obtain the point cloud $[X_w, Y_w, Z_w]$ of the test piece as shown in formula (2), where i is the sensor number.

$$\begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} = \bigcup_i^4 \left(RT_i \begin{bmatrix} 0 \\ f_i(u_i, v_i) \\ g_i(u_i, v_i) \end{bmatrix} + \begin{bmatrix} x_{wi} \\ 0 \\ 0 \end{bmatrix} \right) \tag{2}$$

2.2 Flexible registration

Due to the influence of manufacturing accuracy, sensors cannot be assembled completely according to the designed position, so it is necessary to calibrate the coordinate system relationships between each sensor. The traditional rigid registration algorithm requires feature point pairs to achieve, so this paper constructs multiple sets of center features by placing the ball in different positions. Based on the optimization idea, this paper calculates the rotation and translation matrix from other sensors to sensor 2, as shown in Eq. 3.

$$\begin{aligned} argmin \sum_{k=1}^{m} \| RT_{j\_2} [X_{cij} \quad Y_{cij} \quad Z_{cij}]^T \\ - [X_{ci2} \quad Y_{ci2} \quad Z_{ci2}]^T \|^2, j \\ = 1,3,4, \; i = 1,2,3,4 \end{aligned} \tag{3}$$

Flexible registration needs to consider optimizing the models of each sub sensor, and naturally cannot be constrained solely by the relationship between the center of the sphere, because there are many model parameters for four groups of sensors. If the polynomial of the sensor is of the 5-th order, then considering the system error and registration relationship, there are nearly 200 parameters to be optimized, which requires a lot of positions because the constraint conditions need to be as large as possible than the parameters to be optimized, but such calibration is very time-consuming. Secondly, flexible registration places great emphasis on the overlapping effect of point cloud data in the common parts of sensors. Based on these two reasons, this article proposes to use the surface shape error of the sensor group for different position balls as the optimization objective to carry out flexible registration optimization.

3. Experiment

3.1 System Calibration

Fig. 1 is the experimental system. The displacement stage drives the four sensor modules to move stepwise along the X-axis to push and sweep the part to be tested. The displacement stage has a stroke of 150 mm, an absolute positioning accuracy of 2 μm, and a repeatable positioning accuracy of 1 μm. The camera resolution in the sensor is 1920×1080. The laser light source is 405 nm blue light.

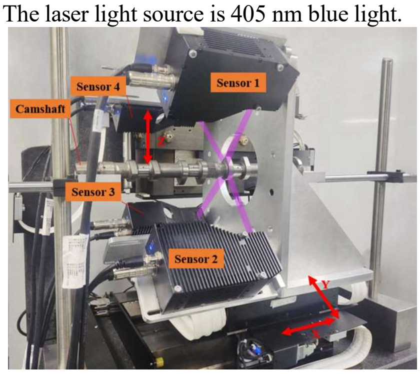

Fig. 1 Experiment system

As shown in Fig. 2(a), the sensor group measures the radius of the ball at different positions. The red line is the flexible registration and the blue line is the rigid registration. It is obvious from the figure that the error is closer to 0 after flexible registration. And the oscillation is significantly weakened. Fig. 2(b) shows the spherical center distance deviation of rigid registration between sensors, because during rigid registration, the registration is carried out with sensor 2 as the reference, therefore, the statistics here are also the registration errors from other sensors to sensor 2. It can be clearly seen from the figure that the average rigid registration error is a minimum of 0.03 mm, and the average flexible registration error is significantly reduced, with a maximum of no more than 0.01 mm. The standard deviation of the flexible registration error is also significantly smaller than the standard deviation of the rigid registration error, both reduced to less than 16.6% of the rigid registration error. Combining Fig. 2(a) and Fig. 2(b), it shows that the flexible registration is more condensed and more like a sphere than the rigid registration.

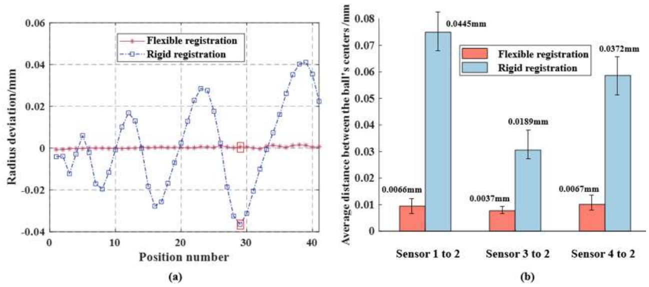

Fig. 2 (a) Radius deviation of the ball at different positions measured after flexible registration and rigid registration respectively (b) mean and standard deviation of rigid registration error and flexible registration error from other sensors to sensor 2

The reason why flexible registration has better accuracy than rigid registration can be found in Fig. 3, where the surface shape error is taken from the flexible registration data and rigid registration data of Group 28 marked in Fig. 3 (a). The rigid registration results obviously have discontinuous surface error distribution at the overlapping position of several sensors, while the flexible registration results have much more continuous surface error distribution at the corresponding position, and the numerical value is much smaller, which shows the effectiveness of the flexible registration. The reason for the improvement of the surface shape error can be found on the right side of Fig. 3. It can be seen that before and after the flexible registration optimization, the measurement surface shape error of the sub-sensor changes in distribution, and the surface shape error becomes smaller and the distribution is more continuous. Therefore, the overall surface shape error will naturally be smoother after the combination.

Through the above experiments, this paper concludes that the original independently calibrated sub-sensor has different surface shape errors, and the surface shape errors of different parts will make the data after rigid registration discontinuous and poor accuracy. However, after the model parameters of the sub-sensor are regulated by flexible registration, the surface shape errors of the sub-sensor are improved. Therefore, compared with the rigid registration, the surface shape errors of the sub-sensor are improved. The data after flexible registration is more accurate and more continuous. The rigid registration results obviously have discontinuous surface error distribution at the overlapping position of several sensors, while the flexible registration results have much more continuous surface error distribution at the corresponding position, and the numerical value is much smaller, which shows the effectiveness of the flexible registration. The reason for the improvement of the surface shape error can be found on the right side of Fig. 3. It can be seen that before and after the flexible registration optimization, the measurement surface shape error of the sub-sensor changes in distribution, and the surface shape error becomes smaller and the distribution is more continuous. Therefore, the overall surface shape error will naturally be smoother after the combination.

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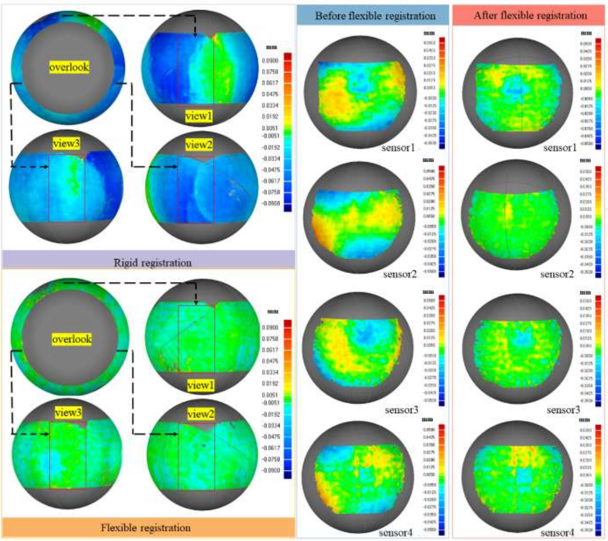

Fig. 3 The surface errors of rigid registration and flexible registration spheres and the surface errors of sub-sensing spheres before and after the optimization of flexible registration

4. Conclusions

For the accuracy of multi-sensor point cloud registration, previous scholars used rigid registration and overlapping point cloud fusion methods on the one hand, but did not correct most non-overlapping point clouds, resulting in low overall measurement accuracy; on the other hand, they optimized and calculated more accurate rotational translation matrix or directly compensated rotational translation matrix according to more dimensional characteristics. However, the accuracy of such methods is not high. In this paper, the idea of flexible registration is proposed, that is, the point cloud accuracy of the whole measurement can be reached to the highest by adjusting the parameters of the sub-sensor model. The experimental results show that the original independently calibrated sub-sensor has different surface errors, which makes the data after rigid registration discontinuous and poor accuracy. By adjusting the model parameters of the sub-sensor, the surface shape error of the sub-sensor is improved, and the surface shape error of the overall measurement data is finally improved, which shows the mechanism and effectiveness of the flexible registration. In addition, compared with rigid registration, the accuracy of the sensor group is improved by 80\% after flexible registration, which further demonstrates the effectiveness of flexible registration for improving the accuracy of the sensor group.

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