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Method to automatically register scattered point clouds based on principal pose estimation

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Abstract. Three dimensional (3-D) modeling is important in applications ranging from manufacturing to entertainment. Multiview registration is one of the crucial steps in 3-D model construction. The automatic establishment of correspondences between overlapping views, without any known initial information, is the main challenge in point clouds registration. An automatic registration algorithm is proposed to solve the registration problem of rigid, unordered, scattered point clouds. This approach is especially suitable for registering datasets that are lacking in features or texture. In general, the existing techniques exhibit significant limitations in the registration of these types of point cloud data. The presented method automatically determines the best coarse registration results by exploiting the statistical technique principal component analysis and outputs translation matrices as the initial estimation for fine registration. Then, the translation matrices obtained from coarse registration algorithms are used to update the original point cloud and the optimal translation matrices are solved using an iterative algorithm. Experimental results show that the proposed algorithm is time efficient and accurate, even if the point clouds are partially overlapped and containing large missing regions. [DOI: 10.1117/1.OE.56.4.044107]

Keywords: optical scanning; point clouds; registration; principal component analysis; iterative closest point algorithm.

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1 Introduction

The application of the three-dimensional (3-D) surface measurements is widespread in the fields of freeform surface inspection, reverse engineering, industrial design and manufacturing, biomedicine, and 3-D modeling of heritage with applications in the souvenir industry, digital museums, and many others such as computer vision and virtual reality. Various optical measuring techniques have been developed to obtain 3-D surface information of artifacts, such as time-of-flight,[1] computed tomography,[2] laser scanning,[3] photogrammetry,[4] fringe projection,[5] and RGB fringe projection,[6,7] etc. These optical techniques can efficiently capture point clouds of data in terms of density and speed and have their pros and cons and different fields of applications. In most cases, these optical sensors can only obtain partial surface data of the artifact/scene in a single scan due to "line-of-sight" issues and the limited field of view of the optical sensor. In order to build a complete surface measurement of the artifact, it is necessary to collect point clouds acquired from different positions and orientations. These multiview scans require subsequent geometrical alignment into a global coordinate system, as each scan is represented in its own local coordinate system; this problem is commonly called the point cloud data alignment or registration problem. Surface registration is one of the most important and decisive steps in the processing of multiview point clouds data.

1.1 *Previous Work*

The goal of registration/alignment for point cloud data is to find the Euclidean motion between point cloud datasets taken from different views in order to represent them all with respect to a common reference coordinate. We use the terms "registration" and "alignment" interchangeably in this paper. Methodologies that have been practically used to register 3-D point clouds from multiviews can be classified into five categories.

1.1.1 *Exploiting range images themselves*

Many researchers have made efforts to solve the registration problem by exploiting clues involved in the range images themselves. This type of technique usually follows two basic steps: first a coarse registration and then a fine registration. The main goal of coarse registration is to find an initial estimation of the rigid motion between two sets of point clouds using correspondences between both surfaces. Existing techniques that are used to deal with coarse registration can be found in the literature.[8–13] The fine registration algorithm utilizes an iterative convergence optimization process to obtain a more accurate solution when an estimation of the motion is previously known; for example, an initial guess or a rough alignment after the coarse registration can be used for the estimation. The goal of fine registration is to obtain the most accurate solution possible. The most representative methods for fine registration is the iterative closest point (ICP) algorithm[14,15] and its variants. An extensive comparison of fine registration algorithms with accuracy evaluation can also be found in the literature.[16]

1.1.2 *Reference/fiducial marker methods*

The reference markers (RM) can be two-dimensional (circular point marker)[17]or 3-D (sphere)[18] and are usually adhered onto the surface or near the object to be scanned. While the

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optical sensor is taking images from a specific view after camera calibration, the 3-D coordinates of the markers within the view are obtained at the same time. The relative coordinates of two scans can be easily calculated if a minimum of three pairs of RM are visible in both scans.

1.1.3 *Using mechanical devices*

This type of techniques exploit mechanical positioning devices as the translation mechanisms such as turntables,[19] articulated arms,[20] or multijoint robotic arms.[21] In this solution, either the optical scanner or the object to be measured is placed on the mechanical device, and therefore, the geometric transformation between the scans can be computed using the movement parameters of the device. In addition, multisensor coordinate measuring machines (CMMs)[22] have been developed to meet the demands of industrial dimensional metrology. A 3-D optical scanner (for example, laser scanner) is mounted on the CMM ram, the movement of which can be strictly controlled to improve the capability of data acquisition. In comparison with other mechanical devices, CMM rams generally have a better accuracy because of their high precision. This type of solutions works well for some applications, yet it is limited for measuring surfaces with large scale. In addition, the use of extra mechanical devices unavoidably reduces the portability and flexibility of the measuring systems.

1.1.4 *Employing auxiliary devices*

Another set of optical or magnetic devices can also be employed to track the optical scanners' position and orientation to align multiview scans. For instance, Leica[23] or FARO[24] laser tracker combines a camera and a laser tracker to monitor the light-emitting diode or infrared targets fixed on the scanner and thereby determines its position and orientation. The optical/magnetic tracing devices can measure large volume objects and obtain good alignment results. However, the add-on tracing devices are relatively cumbersome and sometimes more expensive than the 3-D optical digitizing system itself. Shi et al.[25] proposed an attitude-sensor-aided method for registration of multiview point clouds. A miniature attitude sensor was fixed on the optical scanner and utilized to record the real-time rotation movement of the scanner. Then, the translation movement can be determined by exploiting the normal vector constraint between the correspondence points. Their method is economical but limited to coarse registration of point clouds.

1.1.5 *Hybrid techniques*

Multiple technologies can also be integrated together to improve the behavior of point cloud alignment. For instance, an optical scanning device is mounted on an industrial robot to realize automatic scanning and registration. In the literature,[26] a mobile robot that is equipped with a photo camera and a laser scanner was used for automatic 3-D reconstructions of cultural heritage sites. The robot's poses (position and orientation) were used to obtain a coarse registration of two point clouds and the ICP algorithm was exploited to seek a fine solution. In addition, GOM ATOS system integrates photogrammetry and fringe projection techniques to measure large scale objects. A high-resolution single lens reflex camera is used to take images and compute the 3-D coordinates of the reference points while triple scan sensor is exploited to scan the surface to obtain detailed information. All images will subsequently be automatically aligned into one common coordinate system. This method avoids the accumulative transformation errors and results in a higher accuracy of measuring data.

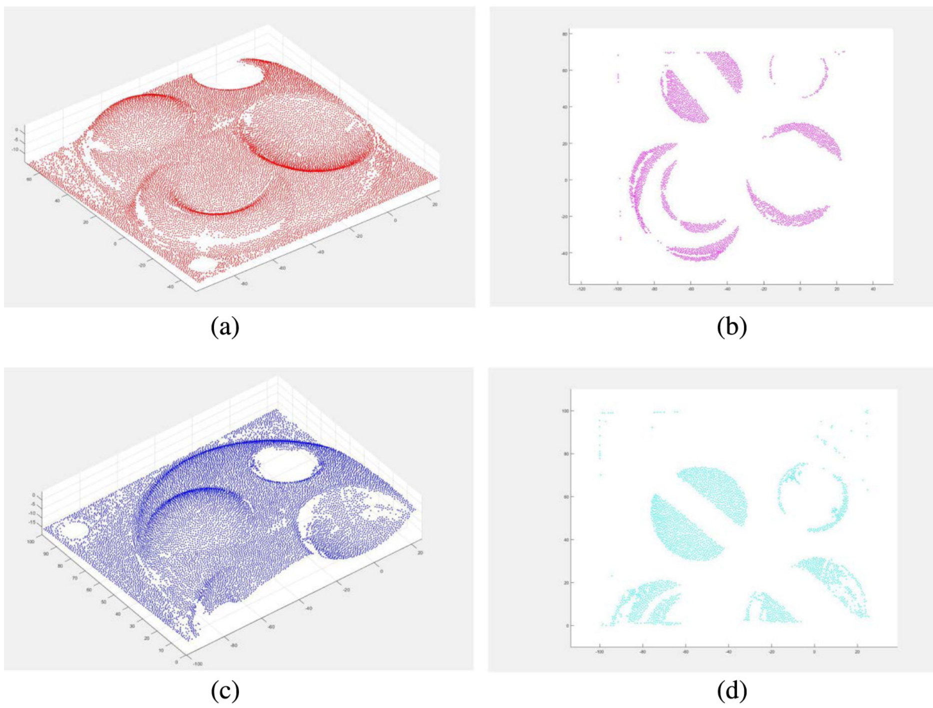

Fig. 1 Feature extraction using the method presented in the literature[29] (most figures in this paper are best viewed in color): (a) fixed point cloud, (b) sample points extracted from fixed points, (c) moving point cloud, and (d) sample points extracted from moving points.

However, many applications in practical use demand accurate alignment point clouds without a prior knowledge of the pose of the views. Therefore, this problem can only be solved by exploiting the clues residing in the range images or point clouds themselves.

Numerous efforts have been made to solve registration problems by finding the optimal transformation between scans by exploiting the clues residing in the range images or point clouds. This process is usually performed in two steps: first a coarse registration, followed by a fine registration. Coarse registration can be performed manually or automatically and the fine registration can be realized using the ICP algorithm. The main problems concerning fine registration, such as convergence to local minima problem and expensive computation time, are greatly dependent upon a proper initial estimate of the rigid motion, i.e., an acceptable coarse registration result.

The traditional method for coarse registration is the manual method; at least three common points are identified and selected in overlapping areas of point clouds, then the transformation can be calculated using the method introduced in the literature.[27]

For automatic coarse registration techniques, spin image matching[28] and RANSAC-based DARCES[12] have been developed to roughly register the point data. The technique presented by Gelfand et al.[29] has also been used to select the common sample features in the pairwise point cloud to constrain unstable transformations, which can be exploited to minimize alignment uncertainty and roughly register point clouds. Mian et al.[30] proposed a coarse registration method using feature matching, their method are based on the 3-D model recognition and segmentation. These methods seek clues by analyzing and extracting features from the range images or point clouds themselves. These methods work well when the point clouds include abundant features and textures and contain adequate overlapping regions of points. However, the artifacts, we intend to measure and register, do not possess such features or textures. Figure 1 shows the example of feature extraction results of National Physical Laboratory (NPL) freeform standard [see Fig. 5(b)] using the method presented in the literature,[29] we can see that this method does not generate a satisfactory result, which means the sampled feature points cannot provide a correct trend for the best convergence of the ICP algorithm. In general, the methods presented by above authors do not seem to provide an ideal solution for our cases.

In addition, the method of genetic algorithm[31] and principal component analysis (PCA)[32] have also been used for coarse registration. One main issue for genetic approaches is the high computational cost, especially when a large number of points are involved in the computation.[16] In the literature,[33,32] the method of PCA are used as an initial guess for a further fine registration. In general, PCA is very fast with respect to other coarse solutions. However, the main problem of PCA is that it obtains accurate solutions when those scans contain a major portion of the actual object. In addition, the principal axes calculated from the first view may have a huge deviation with the second one because of the variance of point distribution. This means the obtained registration result may be completely different from the correct solution, which makes this method unstable in practical use.

1.2 *Motivation*

In this paper, we focus on developing a method for automatic method for alignment of rigid unordered point clouds from multiviews. The specific requirement is to register unordered scans from freeform surfaces; specifically, those artifacts are lacking in features, for example, near net shape (NNS) metal parts. Therefore, a methodology is proposed for automatic registration of these types of surfaces. The alignment methodology is performed in two steps: first, the principal pose of point clouds is evaluated; a proper coarse registration can be obtained by the principal pose information; then, the ICP algorithm is exploited to find an optimal solution and finely register the point sets.

The main contributions in this paper are:

1. A coarse registration methodology is proposed to register 3-D point clouds according to their overlapping sections.
2. An automatic framework is provided to register unordered scattered point clouds without any manual operation or initial pose information of point clouds.
3. The proposed algorithm can precisely register the partially overlapped point clouds, which may contain large regions of missing points. The method is more robust than feature-matching-based methods when dealing with point clouds lacking in prominent or abundant features.

In the following sections, the principles of the methodology will be explained, and its performance will also be evaluated via experiments.

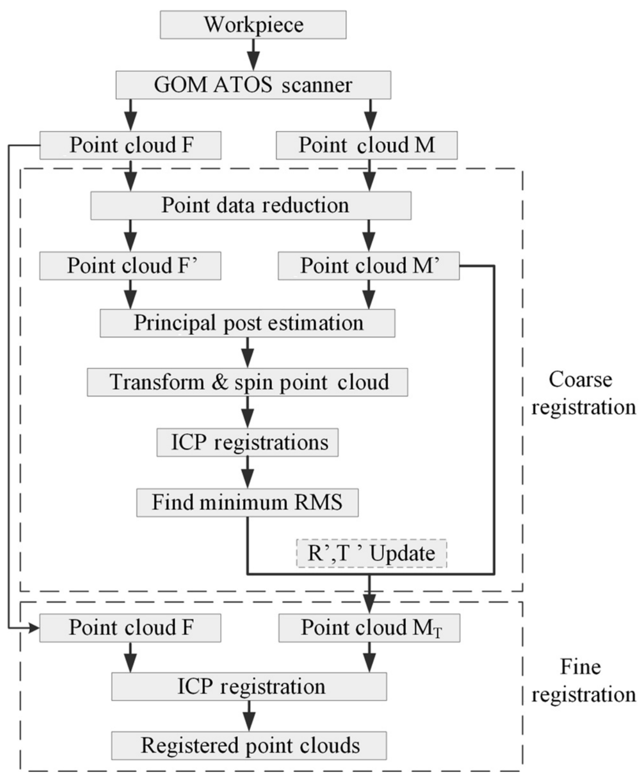

Fig. 2 Framework of the proposed methodology.

2 Method Overview

In the proposed measuring strategy, we can change the scanner to different positions and orientations to cover the full surface of object; alternatively, we can move the artifact with scanner in a fixed position and orientation. Multiview point clouds can then be obtained and aligned by the proposed method.

2.1 *Principal Pose Estimation*

In our method, first of all, we need to evaluate the principal pose of the point clouds. The principal pose of a point cloud comprises the location and orientation information in the 3-D space, which can be represented by its centroid and three principal axes.[34] The centroid of point cloud indicates its location information while the three principal axes represent its orientation information. The centroid can be easily calculated by averaging the coordinate of the points.

In the traditional sense, PCA is a statistical method that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (or principal modes of variation).[35] In our cases, PCA can be exploited to compute the most meaningful basis to re-express the unordered point sets. In addition, it is fast in terms of computation speed and easy to implement. Therefore, the PCA method is selected to obtain the principal pose estimation in this methodology.

2.2 *Proposed Method*

In this study, we scan the part and the first obtained dataset is defined as F (fixed point cloud); then we fix the scanner and move the part and do the scanning again, and its corresponding dataset is defined as M (moving point cloud). We fix point cloud F and move point cloud M to find its optimal transformation matrix respect to F. First of all, we reduce the number of points. PCA is used to estimate the principal pose of both point clouds. The reduced point clouds F' and M' are roughly aligned using estimated parameter matrices until the algorithm converges. The aim of this step is to roughly align the pairwise point clouds. Then, point cloud M_T can be updated from M using the rotation matrix R' and translation vector T', which are obtained from coarse registration result. Second, point clouds F and transformed M_T are reregistered using the ICP algorithm to obtain the final rotation matrix R and translation vector T. The systematic framework of the proposed methodology is shown in Fig. 2.

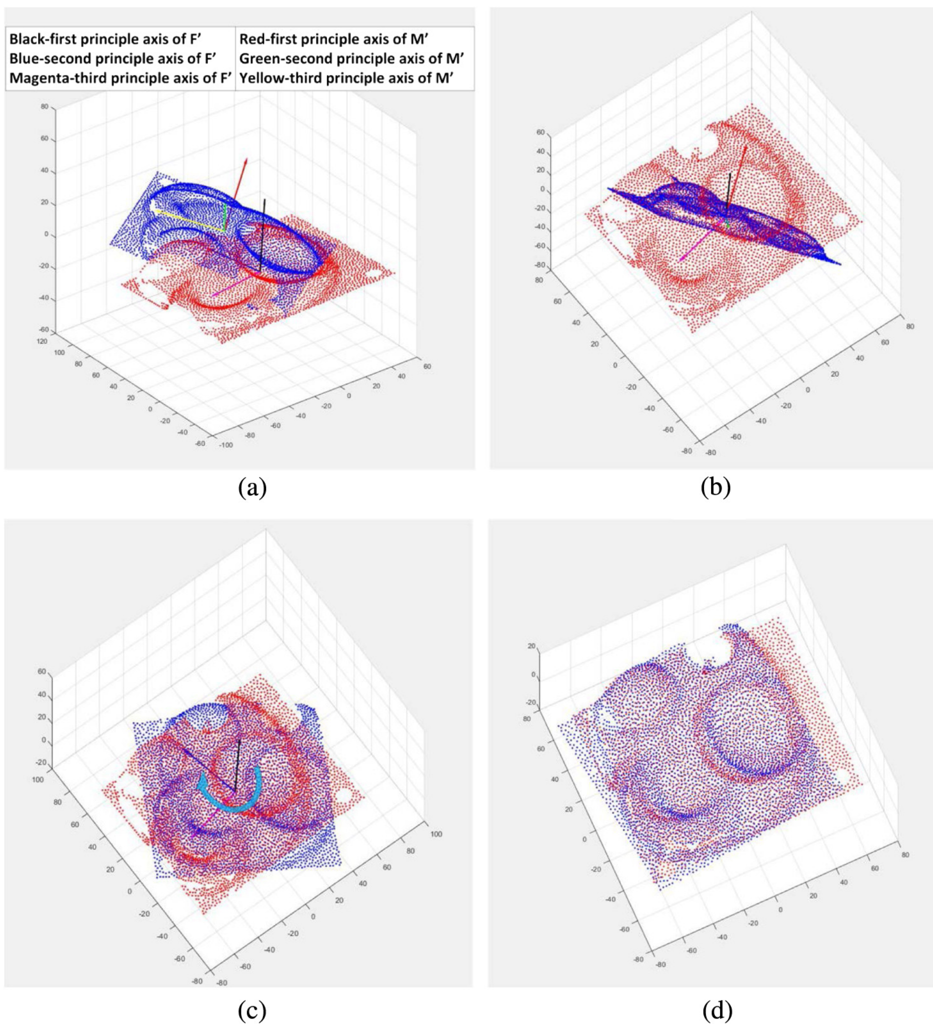

Fig. 3 Point clouds coarse registration using PCA: (a) principal pose estimation using PCA, (b) origin alignment, (c) rough alignment and spin, and (d) coarse registration.

3 Automatic Coarse Registration Based on Principal Component Analysis

First of all, the points are reduced to 10% to 25% of the original point cloud. In this paper, a uniform method is used to reduce the size of point clouds. In this example, we retain one point in four consecutive points. The key features of the original point cloud can usually well maintain and by doing this more than 50% computing time can be saved according to our experiments results.

3.1 *Initial Estimator Using Principal Component Analysis*

We suppose P is a N-point 3-D dataset acquired by a scanning system, then P is a $3 \times N$ matrix. $p_i = [x_i, y_i, z_i]^{\mathrm{T}}$ is an arbitrary point in P. The principal axes can be computed using PCA as the following four steps:[35]

1. Calculate the origin of the principal coordinates system, which is determined as the centroid of P

$$o_P = \frac{1}{N}\sum_{i=1}^{N} p_i. \tag{1}$$

2. Compute the 3×3 covariance matrix M_P from P

$$M_{\mathrm{cov}} = \sum_{i=1}^{N}(p_i - o_P)(p_i - o_P)^{\mathrm{T}}. \tag{2}$$

3. Compute the eigenvector of M_{cov}; the first principal axis is the eigenvector corresponding to the minimum eigenvalue. The other two principal axes are obtained from the remaining two eigenvectors.
4. The X- and Y-axes of the principal coordinate system are defined along the first and the second principal axes, respectively. The Z-axis can then be determined by the right-hand rule.

3.2 *Automatic Coarse Registration Process*

In this example, the point cloud F is fixed and point cloud M is moved to register to F. The specific algorithm follows these logical steps:

1. Calculate the principal axes of the point clouds F' (reduced point cloud in red) and M' (reduced point cloud in blue) using PCA, separately [Fig. 3(a)].

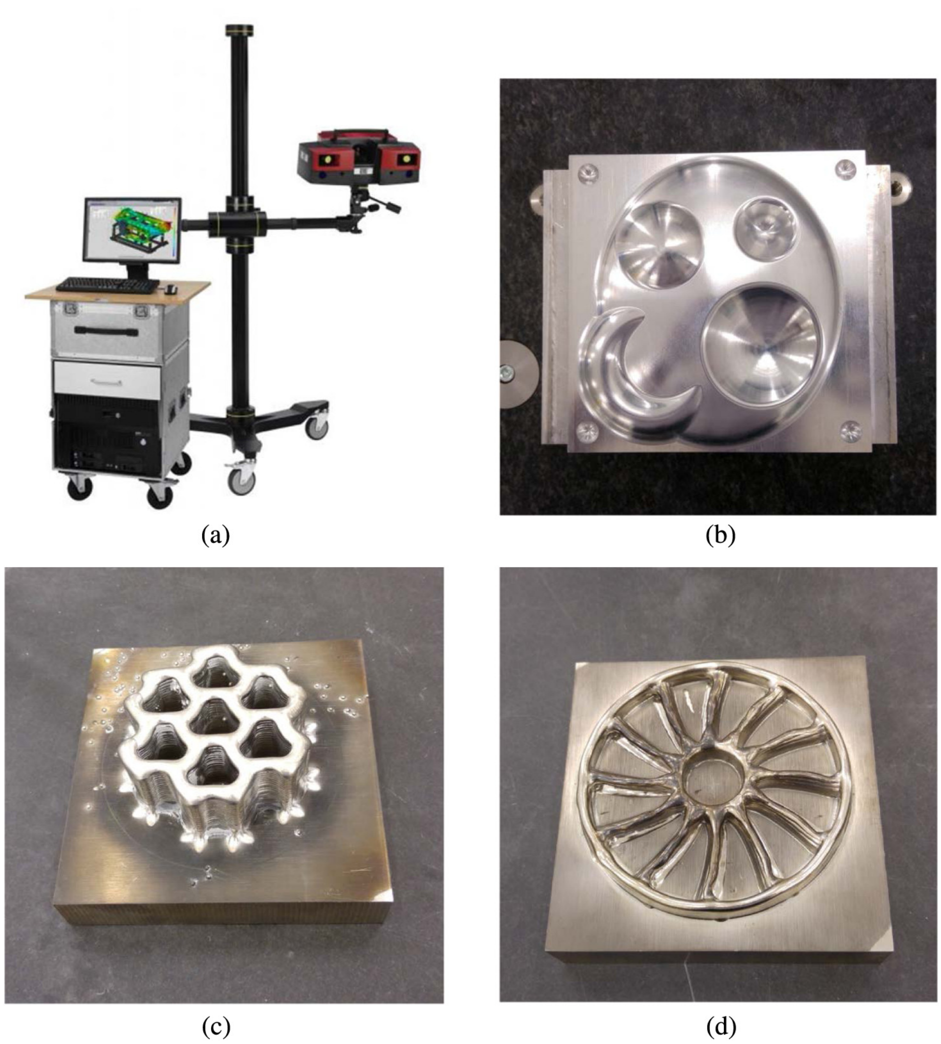

Fig. 4 Elements of the test: (a) GOM ATOS III Triple Scan, (b) artifact one: NPL freeform standard, (c) artifact two: NNS Trefoil, and (d) artifact three: NNS Blade.

Table 1 The configurations of GOM ATOS III Triple Scan.

Camera pixels	8 megapixel (each) ×2
Measuring volumes for small objects	$38 \times 29 \times 15$ to $320 \times 240 \times 240$ mm^3
Point spacing	0.01 to 0.61 mm
Working distance	490 to 2000 mm
Operating temperature	5 to 40°C

Table 2 The number of points before and after reduction.

	Fixed point cloud	Moving point cloud
Original points	15,320	14,850
Reduced points	3828	3697

2. Translate the point cloud M' to F' using the calculated origin [Fig. 2(b)] and then rotate F' by aligning the principal axes [Fig. 3(c)]. We can see that the initial alignment is not very successful due to the complexity of the surfaces to be registered, which may result in an incorrect trend for the later fine registration.
3. Apply the ICP algorithm to register the point clouds and calculate the root mean squares (RMS) result; the maximum number of ICP iterations is set to 50 for each alignment attempt to save computation time.
4. Clockwise spin point cloud M' $\pi/4$ rad along the first principal axis of F' and execute step 3; totally carry on spinning seven times.
5. Find the minimum of RMS and output its corresponding transformation parameters R' and T'; Fig. 3(d) shows an example of coarse registration results.

According to our tests, 50 iterations for coarse registration are enough to determine whether the coarse alignment result can provide a correct trend for the fine registration or not. We select $\pi/4$ as the increment because a satisfactory coarse registration can be obtained in most cases according to the test results, which is a good compromise between registration accuracy and computation burden.

3.3 *Residual Computation*

We defined the residual using the RMS, which is the parameter to evaluate the alignment results. The RMS can be calculated by

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{N} [d(p_i^F, p_i^M)]^2}{N}}, \tag{3}$$

where p_i^F is a point in point cloud F, p_i^M is the corresponding point in dataset M, which can be obtained after execution of the ICP algorithm. $d(p_i^F, p_i^M)$ is the distance between p_i^F and p_i^M, and N is the number of those sampled points.

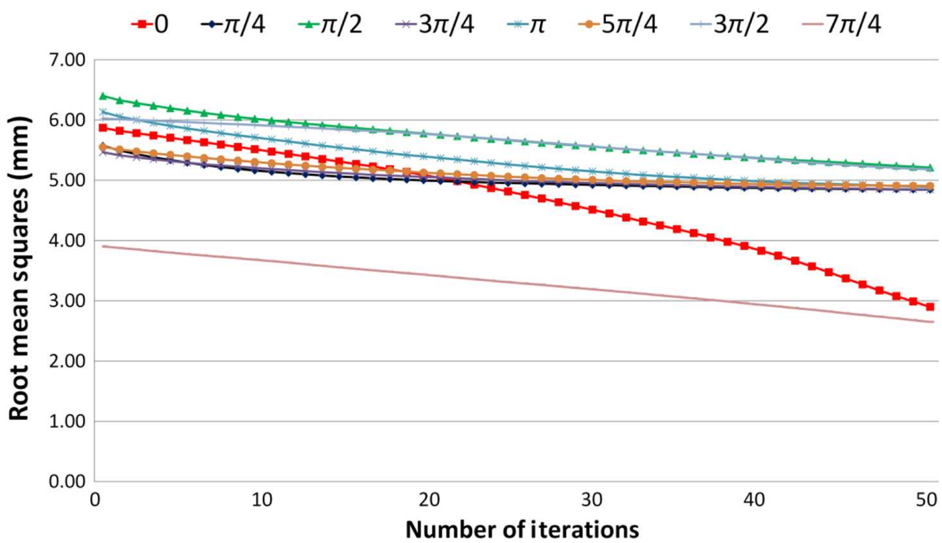

Fig. 5 RMS of coarse registration for artifact 1.

Table 3 RMS of coarse registration for each pose.

Unit: mm	0	$\pi/4$	$\pi/2$	$3\pi/4$	π	$5\pi/4$	$3\pi/2$	$7\pi/4$
Artifact 1	2.8986	4.8440	5.2108	4.8454	4.8891	4.9068	5.1805	**2.6498**
Artifact 2	4.9058	**4.4216**	10.3726	11.7543	9.8921	8.9987	9.2064	11.1579
Artifact 3	4.2479	2.8392	2.4334	**1.8963**	4.3840	4.2684	4.3265	4.0857

4 Fine Registration of Point Clouds Data Using the Iterative Closest Point Algorithm

After the coarse registration, the transformation matrices R' and T' can be used to adjust the location and position of original point cloud M

$$M_T = M \times R' + T'_N, \tag{4}$$

where T'_N is a $3 \times N$ matrix created from T'.

Then, the original point cloud F and updated point cloud M_T can be re-registered to obtain the optimal solution using the ICP algorithm. In this paper, kd-tree[36] is used to speed up the algorithm in order to improve the efficiency of searching speed of neighbor points.

After finding the dataset F_C in point cloud F and its corresponding dataset M_C in point cloud M_T, the singular value decomposition (SVD) method[37] is exploited to solve the rotation matrix R. The algorithm is described as follows:

1. Define matrix H

$$H = \sum_{i=1}^{N} (f_i - o_F)(m_i - o_M)^{\mathrm{T}}, \tag{5}$$

where f_i and m_i are arbitrary point in the point sets F_C and M_C, respectively; o_F and o_M are centroids of F_C and M_C, which can be calculated using Eq. (1).

2. The SVD of H can be represented as

$$H = U\Lambda V^{\mathrm{T}}. \tag{6}$$

U and V are the unit matrices of singular vectors of H. Λ is a diagonal matrix

$$\Lambda = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_r), \tag{7}$$

where $\lambda_i (i = 1,2, \ldots, r)$ is the singular values of H and $r = \mathrm{rank}(H)$ is the rank of H.

A unit orthogonal W is defined as

$$W = UV^{\mathrm{T}}. \tag{8}$$

W satisfies the constraint $\det(W) = 1$. If $\det(W) = 1$, W is the desired rotation matrix R. Then, Eq. (8) can be revised to solve R

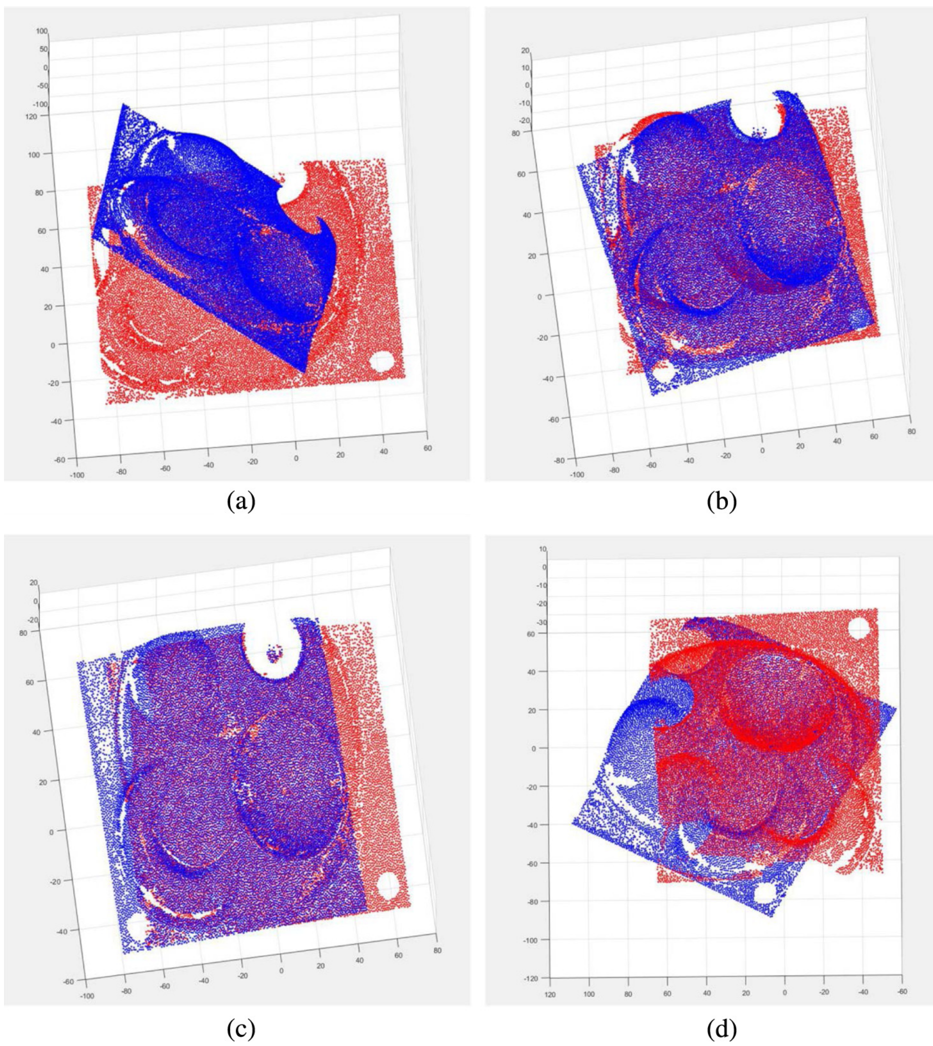

Fig. 6 Point clouds fine registration using ICP (artifact 1): (a) original point clouds, (b) updated point clouds, (c) fine registration results, and (d) incorrect alignment results.

$$R = U \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \det(UV)^{\mathrm{T}} \end{bmatrix} V^{\mathrm{T}}. \tag{9}$$

Translation matrix can be calculated by

$$T = o_M - R \times o_F. \tag{10}$$

In the fine registration, the maximum number of iterations is set to 100. In practice, normally far less iterations are required, due to a good initial alignment from the coarse registration.

5 Experimental Implementation

Both equipment and artifact are soaked in a temperature-controlled metrology room for at least 24 h, with the environmental temperature controlled at 20 ± 0.5°C. The proposed method has been programmed using MATLAB R2015a and tested on a laptop with Intel® Core™ i5-3320MQ CPU at 2.60 GHz and 8 GB RAM.

5.1 *Elements of the Test*

The data are acquired using GOM ATOS III Triple Scan [Fig. 4(a)][38] and its main system configurations are shown in Table 1.

Three artifacts are used to test the feasibility of the algorithm and are show in Figs. 4(b)–4(d), respectively.

5.2 *Experiment Results and Analysis*

The original point clouds of artifact one [Fig. 6(a)] are reduced (see Table 2) and registered using coarse registration method. The point clouds are first aligned using PCA then spun $\pi/4$ rad, the ICP algorithm is executed after each

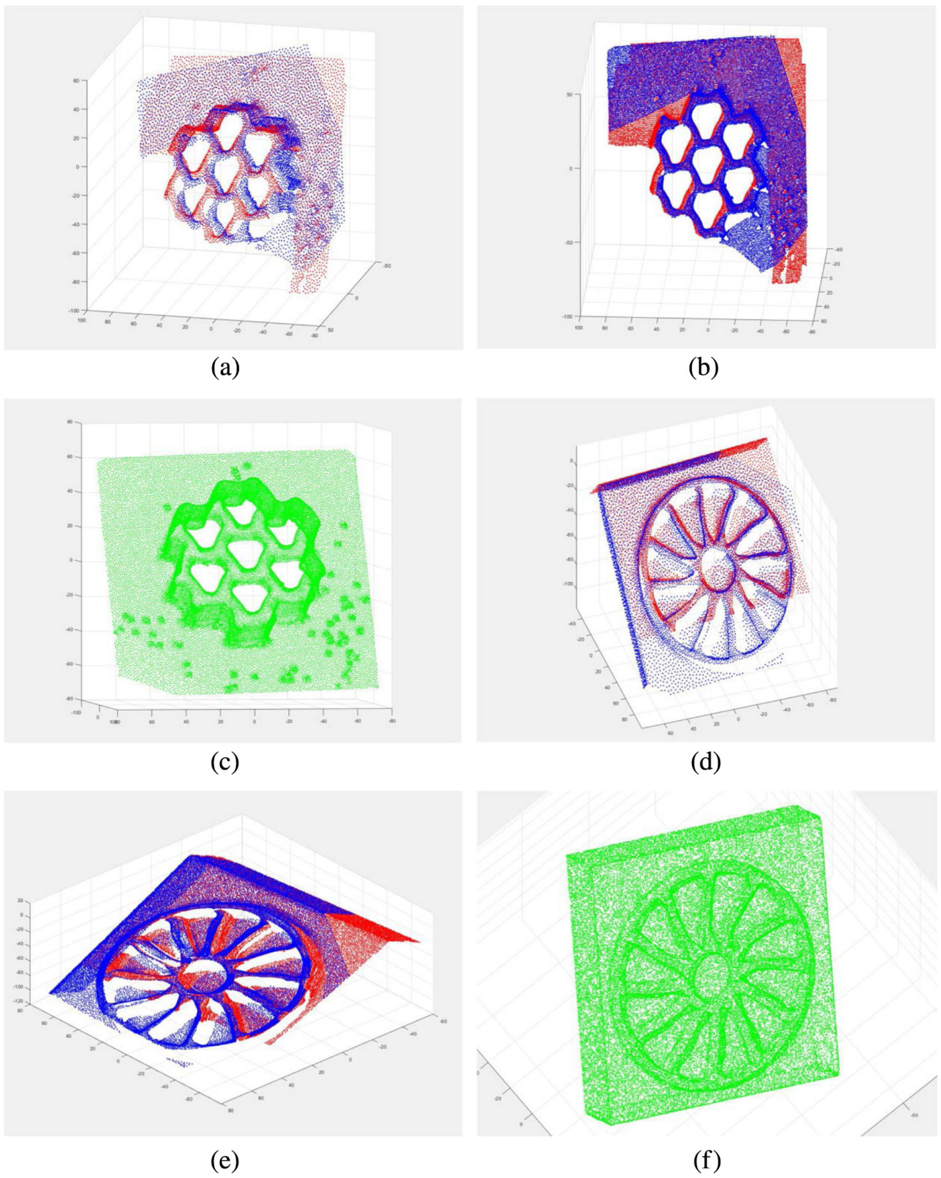

Fig. 7 Registered point clouds (artifacts 2 and 3): (a) coarse registration: artifact 2, (b) fine registration: artifact 2, (c) completed model: artifact 2, (d) coarse registration: artifact 3, (e) fine registration: artifact 3, and (f) completed model: artifact 3.

spinning. The RMS of coarse registration for artifact one is shown in Fig. 5.

Figure 5 shows the $7\pi/4$ rad provides the best RMS, then its corresponding rotation and translation matrices will be selected to update the original point cloud M. We can also conclude that the convergence trend and results directly relate with the initial pose of the point cloud; which indicates the effectiveness of our proposed method. Table 3 lists RMS of coarse registration for all three artifacts in different poses.

After coarse registration, the minimum RMS results (bold values in Table 3) and their corresponding rotation and translation matrices can then be used to update the original moving point clouds. We can see that the point clouds of artifact 1 have already been roughly aligned after updating, as shown in Fig. 6(b). The final registration result is shown in Fig. 6(c); the point clouds have been precisely registered. However, if we do not apply coarse registration step and implement the ICP algorithm straightforwardly, the alignment cannot obtain a correct result even the iterations number is set to 100 [see Fig. 6(d)]. Artifacts 2 and 3 were also scanned and tested using the proposed algorithm, as shown in Fig. 7.

The RMS results of coarse and fine registration for the three parts are listed in Table 4. The RMS results indicate that the algorithms provide accurate registrations even if the point clouds are only partially overlapped and contain large missing regions.

If we apply PCA to coarse registration and implement the ICP algorithm for fine alignment, the registration results are given in Table 5. Obviously, the alignments cannot obtain accurate results using PCA, and our method provides registration results with much better performances as shown in Table 4.

The computation time for both coarse and fine alignment using the proposed method are presented in Table 6. We can see that the computing speed is fast and satisfactory.

Table 4 RMS of alignment using our method.

Unit: mm	Artifact 1	Artifact 2	Artifact 3
Coarse registration	2.6498	4.4216	1.8963
Fine registration	0.0204	0.0198	0.0186

Table 5 RMS of alignment using PCA.

Unit: mm	Artifact 1	Artifact 2	Artifact 3
Coarse registration	2.8986	4.9058	4.2479
Fine registration	0.0522	0.0592	0.5686

Table 6 Computation time for each example.

Unit: s	Artifact 1	Artifact 2	Artifact 3
Coarse registration	1.69	4.55	3.28
Fine registration	2.88	4.15	3.39

6 Conclusion

According to the authors' knowledge, despite extensive previous research in the field of registration, the automatic alignment of unordered points has not yet been well solved for situations in which the point clouds lack abundant features. The coarse registration heavily depends on the initial estimation of transformation matrices, which plays a vital role in the whole alignment process and will ultimately determine the accuracy of fine registration results. In this paper, an automatic alignment algorithm for unordered scattered point clouds, based on PCA, is proposed. The proposed method can automatically solve the partially overlapping 3-D registration problem for unordered point clouds, without any initial pose information or manual operation.

First, original point clouds are reduced to save computation time; the principal poses of point clouds are estimated using PCA method and aligned using centroids and principal axes. Second, the initial estimations for transformation matrices are acquired by coarse ICP registration algorithm, then the moving point cloud is spun $\pi/4$ incrementally and the RMS is recalculated. Third, all eight RMS are calculated to find the minimum RMS; its corresponding rotation matrix and translation vector will be output as the coarse registration results. Finally, the original moving point cloud is updated using transformation parameters obtained from coarse registration; the optimal rotation and translation matrices of the fixed point cloud and the updated moving point cloud are recalculated by the iterative algorithm.

The main limitation of the use of PCA for coarse registration is that it obtains accurate solutions when point clouds contain a major portion of the actual object. In practical tests, our method can achieve a satisfactory result if the overlapping of the region is 50% or more. More important, our algorithm can be used with effectiveness with surfaces that do not contain prominent features, in contrast to feature-based alignment methods. Three testing artifacts are used to verify the feasibility of the proposed method, and the testing results show that the algorithm is accurate and efficient with regard to computational time. In addition, the data preprocessing techniques, e.g., data filtering and data ordering, can be used to reduce noise and improve the quality of point clouds. Our algorithm can be applied to the raw 3-D point data straightforward and the scanned data do not need to be preprocessed, which further proves the reliability of the method.

Acknowledgments

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