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ORIGINAL ARTICLE

Automated inspection of aircraft parts using a modified ICP algorithm

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Abstract The application of computer-aided inspection integrated with the coordinate measuring machine and laser scanners to inspect manufactured aircraft parts using robust registration of two-point datasets is a subject of active research in computational metrology. This paper presents a novel approach to automated inspection by matching shapes based on the modified iterative closest point (ICP) method to define a criterion for the acceptance or rejection of a part. This procedure improves upon existing methods by doing away with the following, viz., the need for constructing either a tessellated or smooth representation of the inspected part and requirements for an a priori knowledge of approximate registration and correspondence between the points representing the computer-aided design datasets and the part to be inspected. In addition, this procedure establishes a better measure for error between the two matched datasets. The use of localized region-based triangulation is proposed for tracking the error. The approach described improves the convergence of the ICP technique with a dramatic decrease in computational effort. Experimental results obtained by implementing this proposed approach using both synthetic and practical data show that the present method is efficient and robust. This method thereby validates the algorithm, and the examples demonstrate its potential to be used in engineering applications.

Keywords CNC · CMM · Point datasets · ICP · Hard registration · Soft registration · Part inspection

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Nomenclature

$\left\{\overrightarrow{M}_i\right\}$	CAD Model coordinate
m_1, m_2, m_3 and m_4	Four closest points in CAD dataset M
$[\boldsymbol{q}_0, \boldsymbol{q}_1, \boldsymbol{q}_2, \boldsymbol{q}_3]$	4D vector
$\left\{\overrightarrow{P}_i\right\}$	Part inspection coordinate
$\mathbf{R}$	Rotation matrix
$\boldsymbol{T}$	Translation vector
$\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{d}$	vectors of $\{x_i\}$, $\{y_i\}$, $\{z_i\}$, and $\{d_i\}$, respectively

1 Introduction

The traditional practice in aircraft industries is to inspect precision structural components involving freeform surfaces by using the coordinate measuring machine (CMM). The measurement data obtained from the CMM is compared against the design data to establish the dimensional errors in the manufactured part. A proper correspondence between the measurement coordinate system used for measurement in the CMM and that in the design coordinate system of the part is required to determine the error in the manufactured part and verify its conformity or otherwise to the tolerance specified on the machined part. Presently, this correspondence is established a priori through the use of high-precision reference markers and custom-made jigs. In the case of inspecting parts that are large and contain free-form surfaces (very common in aircraft structure), the sectional inspection approach is adopted, where measurements are made along planar sections and compared with the design data (along the same plane) to determine the pointwise deviations in the machined part. This, however, is only a small improvement over the traditional approach of using physical templates defined at several locations on the surface to inspect the part as the quality of inspection depends on the number and density of the point sets and choice of measurement locations. This sectional inspection method is not desirable, as it is a partial inspection procedure, which, in practice, could lead to difficulty during the assembly. A typical example of a complex oil cooler inlet (shaded in sky blue) and outlet ducts (shaded in yellow and cyan) is shown in Fig. 1a. The sectional curves used for the inspection of these two parts are shown in Fig. 1b. In this case, the oil cooler inlet and the outlet ducts have to match with each other on assembly. The sectional inspections showed that the parts were well within the acceptable tolerance zone. However, the deviations were significantly larger in regions that were not covered by the sectional curves and therefore not inspected. These deviations were revealed during assembly as large unacceptable gaps between the inlet and the outlet ducts.

Today, it is possible to scan entire surfaces using contact and non-contact scanners and generate dense point datasets. Processing this dense data to assess their deviation between the machined and nominal description of the surface is the problem being addressed in this paper.

This paper thus presents an automatic method of carrying out the inspection of aircraft (and indeed any complex) structural component by integrating inspection data from the CMM and establishing its registration with nominal data obtained from the CAD system. The cloud of point samples from the surface of the machined part is typically obtained from measurement along multiple views having different reference datum. The objective of registration is to establish a common datum reference by estimating the transformations between the different datasets. This approach is more practical, as it involves establishing a correspondence between two datasets whose native data are essentially point based and are completely independent of the CAD system. Point clouds being the most fundamental representation of surface and shapes, this approach not only eliminates the need for any translation of data into neutral format such as IGES, STL or STEP but also does away with the need to mathematically define the surface of the manufactured component.

This paper proposes a modification of the popular ICP method to determine the transformation relating to the measured and nominal point set, as the registration of the two point sets is for obtaining the deviations of the measured point data from the CAD description. A new procedure based on approximating the nominal surface in the vicinity of the measure point has been developed to estimate the deviations between the measure points and the CAD data. This procedure provides the foot point on the CAD dataset where the error distance defines the manufacturing error. The results obtained so far are very encouraging.

The remainder of this paper is organized as follows: Section 2 reviews the current state of the art in the registration of point sets. An overview of the automated inspection process implemented is described in Section 3, bringing out clearly the importance of automatic registration of the inspection dataset with the CAD reference frame. Section 4 describes the registration process developed (as a variation of the ICP method) in detail. Section 5 presents results and a discussion on the application of the proposed approach to a couple of actual components. Conclusions and suggestions for further work are presented in Section 6.

2 Literature survey

The usage of devices such as advanced CMMs, laser trackers, articulated arms with scanner, etc. in establishing rapid and automatic inspection of complex components is a recent approach and is an active area of research. In the last

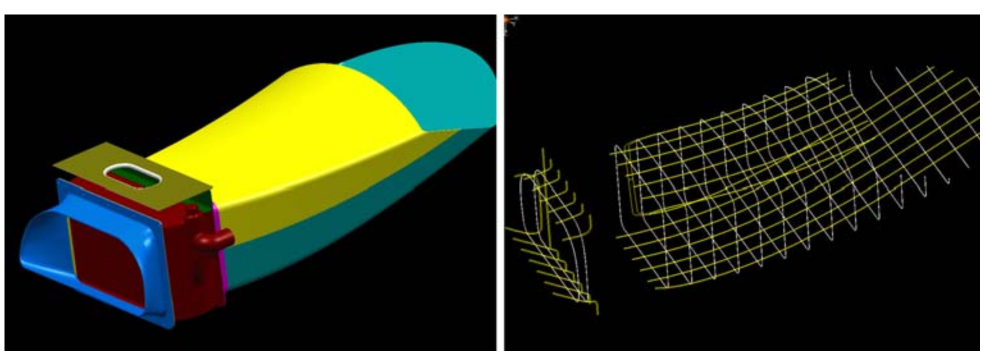


Fig. 1 a Oil cooler inlet and outlet ducts. **b** Sectional inspection curves of oil cooler ducts

a Oil cooler inlet and outlet ducts **b** Sectional inspection curves of oil cooler ducts decade, several efforts have been made concerning the registration of 3D point cloud data. These efforts, however, have thus far been primarily restricted to the areas of computer vision, image processing, and pattern recognition.

The most popular approach to solving the registration problem is the class of algorithms based on the iterated closest point (ICP) technique suggested by Besl and Mckay [1]. This algorithm is a general-purpose registration method for freeform curves and surfaces wherein it is assumed that the data point set is a subset of the model point set. ICP has three basic steps:

1. Pair each point of the object dataset to the closest point in the model dataset.
2. Compute the motion that minimizes the mean square error between the paired point sets.
3. Apply transformation to the object dataset and update the mean square error.

The three steps are iterated, and the iterations have been proven to converge in terms of mean square error. This approach will converge to the nearest local minimum of the sum of the squared distances between the closest points. A good initial estimate of the transformation between the point sets is required to ensure convergence to the correct registration. Incorrect registration may occur if the error in the initial transformation is too large. An extension of this algorithm is now widely used for the registration of multiple sets of surface data.

Chen and Medioni [2] demonstrate the registration of partially overlapping range image data. The distance between the surfaces in the direction normal to the first surface is used as the registration evaluation function instead of the point to nearest point distance. A modified cost function is used to compute the registration, which minimizes the squared distance in the direction of the surface normal. This cost function gives improved rates of convergence, but with a significant increase in computational effort. Zhang [3] proposes a modified cost function based on robust statistics to limit the maximum distance between the closest points to handle the registration of partially overlapping data. This method also requires every point on the object surface to have a corresponding point on the model surface. As mentioned earlier, this assumption may not always be valid. The cost of performing ICP registration depends on the efficiency of the closest point evaluation and uses a K-d tree to partition the point sets. Turk and Levoy [4] have modified the original ICP algorithm to register partially overlapping triangulated meshes constructed from range image data. Nearest point correspondences are not used if either point is on the mesh boundary or the distance between them exceeds a certain threshold. To achieve efficient local search, a uniform spatial subdivision to partition the set of mesh vertices is carried out. An earlier effort by Arun et al. [5] also assumes a one to one correspondence between two point sets. They use singular value decomposition (SVD) to find the transformation (rotation and translation) given the correspondence between points. In this method, the unknown translation parameters involve the shifting of object point sets to the center of gravity of model data point sets, calculating the unknown rotation matrix using the SVD of a 3×3 matrix and finally calculating the translation parameters. Horn [6] also reports a similar method based on unit quaternion developed independently around the same time.

Umeyama [7] proposes a theorem, which gives the least squares estimation of similarity transformation parameters between two point patterns.

In all the above methods, a priori knowledge of point correspondences is necessary. This is a major limitation, since this is usually not available in normal practice. In addition, when the object and model datasets are initially grossly misaligned, the convergence of the ICP algorithm cannot be guaranteed (Ristic [8]), and thus necessitates bringing the two point sets closer as a first alignment step. This step is functional only if the object dataset is part of the model dataset, and the outliers need to be eliminated.

Ko [9] has addressed the problem of free form object matching using global and partial matching with scaling effects. He handles the registration of points with respect to a non-uniform rational B-spline (NURBS) surface and a NURBS surface with respect to another NURBS surface when no a priori information on correspondence or initial transformation is provided. Two approaches, one involving umbilical points and the other as Gaussian and mean curvatures, have been considered. Using either one of these, the two objects are aligned as closely as possible. The solutions are proposed for applications in the area of copyright protection.

Gelfland et al. [10] describes an algorithm for the automatic alignment of two 3D datasets without any assumption on their initial positions. The algorithm computes a volume descriptor for each surface point based on local geometry, and for each feature point on the data, the descriptor values are used to find the potential corresponding points. A fast branch and bound algorithm based on distance matrix comparisons is employed to select the optimal correspondence set, which brings the two shapes into a coarse alignment. This is used as an initialization step to first carry out ICP and then its variants to carry out fine registration of the object data with model data.

Bispo and Fisher [11] adopted a modified version of ICP that uses a priori knowledge of an approximation of the right registration, thus making their method more robust to outliers. They propose the use of a smaller set of measured data points to reduce the computational effort. Masuda [12] proposed a method to register multiple range images using the signed distance field, which is a scalar field determined by the signed distance of an arbitrary 3D point from the object surface and which assumes that the input data have been roughly preregistered.

Gruen and Akca [13] have proposed a least squares 3D surface and curve matching technique where the point cloud derived by any method is treated as a surface-matching problem and, in particular, as least squares matching of overlapping surfaces. This method attempts to match one or more 3D search surfaces to a 3D template surface, thus minimizing the sum of squares of the Euclidean distances between the surfaces.

Pottmann et al. [14] have proposed an alternative concept of registration without ICP, which relies on instantaneous kinematics and the squared distance function on the surface geometry.

While the ICP technique and its variants are still the preferred technique to register two datasets, the following problems still remain with the technique: time complexity associated with the identification of the closest points; a priori knowledge of an approximate registration between the two datasets, which is required to overcome the problem with outliers and prevent convergence to local minima [11]; and a one point set being assumed to be a subset of the other in most techniques [13].

Most of the work mentioned in the literature has reported the use of this (ICP) technique to match images in the domain of image processing. The other notable work within the realm of image processing not based on the ICP technique is by Tian et al. [16] and uses the identification of interest points for stitching the image mosaic taken from different viewpoints. However, in inspection, while the data from the inspection device is a set of points, the dataset with which comparison needs to be done has to be either a smooth representation of geometry or a sampling of points from it. A sampling from the tessellated representation of the surface has been used for registration [17]. A tessellated representation of a surface cannot be used in all cases (including complex aircraft parts), as the inbuilt tessellation error is not accounted for in these approaches. Nevertheless, this methodology is more suited to image-based registration rather than to the area of computational metrology. In the context of automated inspection or computational metrology, the restrictions imposed on the point sets to use the ICP technique do not hold, in particular, the one requiring the points in one set to be a subset of the other or match them in number since neither of them can be ensured. The metric for error in the registration also cannot be based on the distance between points. There have been other metrics proposed in the literature, for example, Park and Subbarao [18]; however, none of these approaches has been used in the context of inspection.

3 Automatic inspection of parts

As mentioned earlier, the traditional practice in inspecting complex parts involves the use of templates or gauges that define the acceptable geometry in local regions of the part (templates, for example, are defined at different sections of a part.) Gauges, usually, are in pairs (e.g. "go-no go" gauge)—one that has to fit and the other that should not fit a matching feature in the part, thus capturing the range of acceptable sizes. With the advent of CMMs, two scenarios are possible.

In the first, the part to be scanned by the CMM is positioned in a well-defined manner using external jigs, fixtures, or additional features that are built into the part for the specific purpose of locating it. In this scenario, the reference frame with respect to which the inspection data is obtained is well-defined enabling easy comparison with the nominal model. We refer to this as *hard registration* of inspection data.

An alternative to the above is to scan and obtain inspection data from the part when it has been kept in an arbitrary location without the use of any fixtures or markers. In this case, the reference frame in which the inspection data has been obtained has to be matched with the reference frame of the nominal model. We refer to this as *soft registration* of inspection data. The soft registration approach is clearly more desirable, as it is lower in cost (no investments on complex and precision jigs and fixtures), flexible (any part that can be mounted on the CMM bed and can be inspected), and quicker. An additional advantage is that this process also eliminates the need for adding location features, such as a tooling hole reference datum and perpendicularity and parallelism data to parts that have to be trimmed after inspection as shown in Fig. 2. As this process eliminates the need for much of the human intervention required in traditional inspection, the process as a whole lends itself to a high level of automation.

There are two alternatives even with respect to the kind of data collected. Earlier, the inspection probes would scan a part in a discrete manner, thereby gathering relatively sparse data as each contact of the probe with the part surface is first recorded and then is retracted as the probe is moved to the next point. With the analog probes and optical probes now available [19–21], the part can be scanned continuously resulting in the capture of a large amount of data very quickly (This is often referred to as dense data). While using CMMs with continuous probes for inspection, the density of points obtained need not be as large as would need to be the case for reverse engineering applications.

The inspection process using a CMM with a continuous probe is shown in Fig. 3. In the scanning step, point dataset in the inspection coordinate system (ICS) is obtained. The registration step establishes the rigid transformation be-

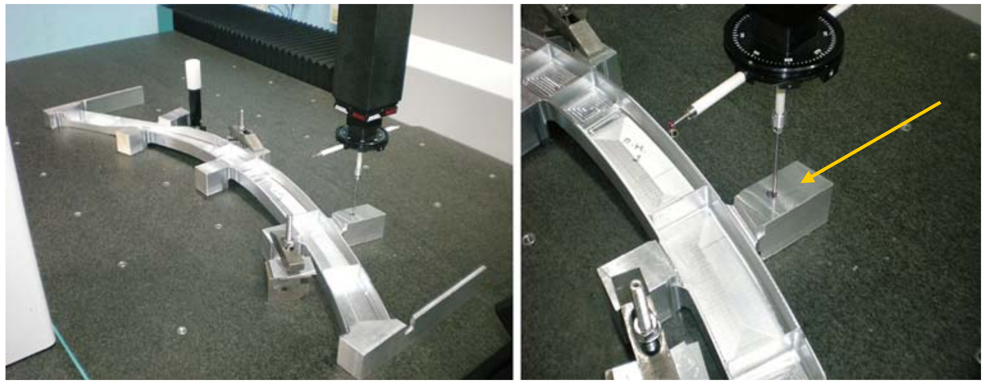


Fig. 2 Tooling hole reference datum on side frame of an aircraft

tween the ICS and the model coordinate system (MCS) in which the nominal CAD model is defined. With both the inspection data and the CAD model data in the same reference frame, it becomes possible to determine the deviations between the inspection data and the nominal model data and check the acceptability of the deviations. This is done in the comparison step.

The acceptability of the deviations is decided by checking if the deviations are within specified tolerances. The tolerance specifications thus constitute the acceptance criteria for the part. In this paper, the inspection criterion defined in Table 1 is used for evaluating the deviations [15]. The criterion consists of tolerances defined for contours/profiles in a plane and for surfaces that are defined using lofting curves.

The deviations between the manufactured part and the nominal model are obtained as one of the outcomes of the registration process. This is described in the next section.

4 Registration method

The registration procedure adopted in this paper is based on the well-known iterative closest point (ICP) algorithm [1]. The ICP algorithm is based on determining the correspondence between points in two datasets. In the present approach, we use the measured points from a CMM to represent the inspection point dataset. The nominal specification of the part is available in the form of a CAD model. Instead of comparing the inspection point dataset with the CAD model, we sample the CAD data to get data points that are used for both registration and comparison. As mentioned earlier, this allows the inspection task to be done independently of the CAD system. The point selection from the CAD model is part dependent, and the density of the sampling should be higher at regions where the curvature varies rapidly.

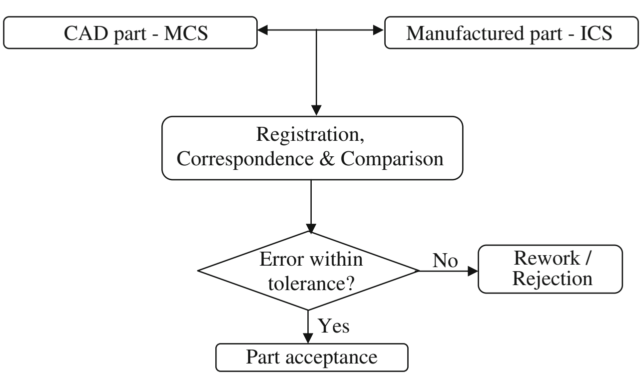


Fig. 3 Schema for automated component inspection

The registration procedure consists of establishing a matching between two sets of three-dimensional point datasets called the part inspection dataset P and the CAD model dataset M, where their point elements are defined as $\mathrm{P} = \left\{\overrightarrow{P}_i\right\}$ for i=1, …N_P and $\mathrm{M} = \left\{\overrightarrow{M}_i\right\}$ for i=1, … N_m where $\mathrm{P_i}$ and $M_i \in \mathrm{Rn}$, where n=3 and $m>p$.

The spatial translation between two sets is a linear transformation vector in R^3 and is the difference in the location of the center of gravity of both the sets. For the rotational alignment of the two point sets, we use quaternion algebra[22].

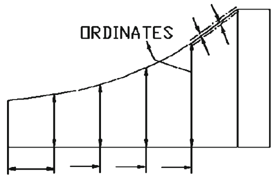
Here, the quaternion is a 4D vector denoted as $\boldsymbol{q}=[\boldsymbol{q}_0, \boldsymbol{q}_1, \boldsymbol{q}_2, \boldsymbol{q}_3]$ and is used to represent the 3D rotation, which is of practical importance to us. The norm of a quaternion $N(\boldsymbol{q})$ is conventionally the sum of the squares of the four components. The 3×3 rotation matrix generated by a unit quaternion is given as

$$R = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\ 2(q_1q_2 + q_0q_3) & \left(q_0^2 + q_2^2 - q_2^2 - q_3^2\right) & 2(q_1q_3 - q_0q_1) \\ 2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_0q_1) & q_0^2 + q_3^2 - q_1^2 - q_2^2 \end{bmatrix} \tag{1}$$

Therefore, the coordinate transformation which involves the rotation matrix R and the translation vector T from the part ICS to the CAD MCS is solved using quaternion algebra wherein

$$M_i = R_i P + T_i \tag{2}$$

Table 1 Tolerance for machined profiles and surfaces



Profiles having contour defined by ordinates	± 0.30mm
Profiles defined by lofted lines	± 0.20mm

where M_i denotes the coordinates in the model frame, and P denotes the coordinates in the part inspection frame. A necessary condition for the current algorithm is that the inspection dataset is assumed to be a small subset of the CAD dataset, which is represented by a large point set within the limits of available computer resources and acceptable accuracy to achieve the desired tolerance.

The process of modified ICP can be classified in two stages:

1. For every point in $\{P_i\}$ $i \in [1, N_P]$, the closest point $\{M_i\}$, $i \in [1, N_m]$ in the CAD model is found.

A fast iterative method is adopted for establishing a correspondence with the closest points. From the surface model, a set of points are sampled and used to establish a correspondence between the inspection points and the sampled CAD points. Depending on the convergence in the second step, the sampling density is refined so that the search for correspondence between the two datasets happens over a larger sample. This procedure allows the determination of a coarse registration at a very low computational effort as the size of the dataset to be searched for correspondence is small. In adition, as seen in Fig. 4, after a certain number of points, there is no appreciable improvement obtained by increasing the CAD point set density. Fig. 4 also depicts CPU time in seconds as a function of sampled CAD points where it is noticed that the time varies linearly with the number of CAD points.

2. The transformation as given in equation (2) above is applied for every point in the inspection points set P_k. The transformed inspection points set at, say, the jth step of iteration are now closer to their corresponding points M in the CAD dataset. The mean squared objective function to be minimized is the distance function given by:

$$d_i = \frac{1}{m}\sum_{K=1}^{m}\left\|T_i P_k^i - M_k^i\right\|^2 \tag{3}$$

The process enumerated in iterative steps 1 and 2 is repeated using the updated inspection point set P_k^j until d_i converges to a predefined threshold tolerance or when a predetermined number of iterations is reached.

In representing the CAD model in the current work, the point dataset on the CAD model is generated as a topologically uniform rectangular grid in the parametric space (u, v). This could be done in almost every known CAD package used to generate the CAD model of the part to be inspected. The least square is calculated between the points in correspondence. The objective function minimized is the sum of the squared distances divided by the number of points in the inspection dataset. Since the points in the CAD set are sampled, the actual error need not be the distance between the points in correspondence or the average of the square of this error. The actual error that is of interest is the normal distance from the part inspection set to the CAD surface, which is obviously not captured in the procedures adopted until now. We define the error as the distance between the inspection point and the surface in the vicinity of its corresponding point in the CAD dataset. The vicinity is defined by the facets between four points in close correspondence with the inspection point. The procedure is illustrated in Fig. 5 below.

Here, M_1, M_2, M_3, and M_4 are the four closest points in the CAD point set M to the part inspection point say P_1.The localized region-based approach captures the normal distance of P_1 to each of these triangles, the minimum of which establishes the closest deviation of the manufactured component to its native CAD geometry. This modified approach eliminates the possibility of two inspection points having the same closest point from the geometry set. This provides a practical approach in finding the absolute

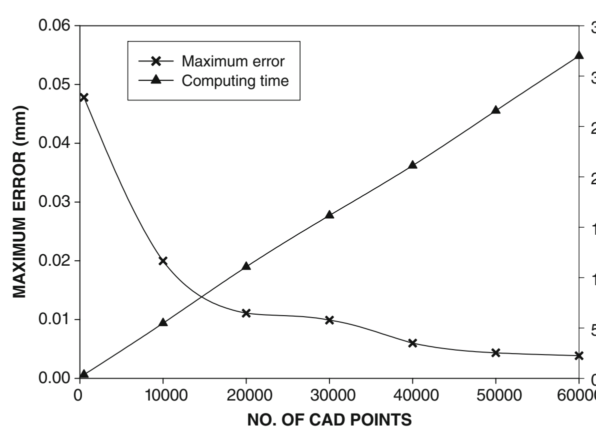


Fig. 4 Convergence of Inspection error with CAD point density

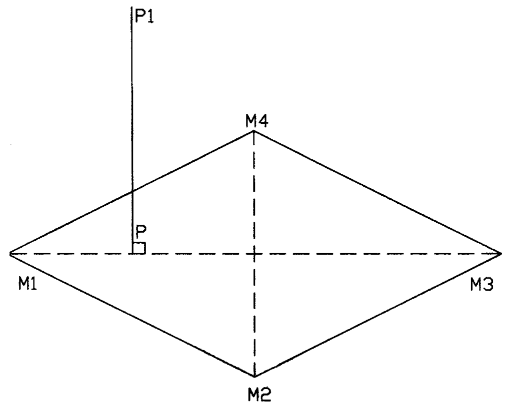


Fig. 5 Local quadrilateral facet

distance error, as the least squares method does not necessarily define the accurate part tolerance deviation as explained above. Computing the distance between the inspection point and the tangent plane at its corresponding point will also not be the right measure for the simple reason that the corresponding point is obtained from a sample and may therefore not be the actual closest point on the surface. The tangent plane at this point may therefore not be the correct approximation of the surface around the closest point. This pointwise distance could be well above the acceptable tolerance, whereas the least square distance may be well below the permitted tolerances in the iterative scheme, thereby leading to the wrong conclusion of accepting the erroneous (out of tolerance) component. Thus, it is more appropriate to use the pointwise distance criterion to establish the manufacturing deviation rather than the least square convergence criterion. This, in a way, confirms the application of the $L\infty$ norm for minimizing the objective function rather than the L_2 norm. Figure 6 shows the maximum and minimum distance for deviations mapped for the absolute error method, the least square distance method, and the closest point method for a typical test case to assess the various convergence criteria. It may be noted that the least square error has reduced to 2.2×10^{-5} mm, whereas the actual maximum deviation is 0.18 mm, which is relevant from the inspection and acceptance/rejection of the component.

5 Results and discussion

The algorithm was evaluated by carrying out multiple cases of inspecting components with 2D and 3D part geometry. The results obtained by inspecting the contour template and a complex free form surface are described separately, demonstrating that the algorithm efficiently satisfies both the cases. This code is run under Microsoft Windows XP with Intel Pentium 3.4 GHz and 2 GB of RAM and takes less than a minute to obtain the inspection results for the belly fairing mold data, which is a typical freeform surface using 60,000 points for the CAD dataset.

5.1 Inspection of space curve

In the manufacturing of fiber-reinforced plastic components using master molds, there are instances wherein a large number of sectional contours have to be inspected for accepting the part. This is in addition to the inspection of the surface along the generative direction. This is also an important and common requirement in the manufacture and inspection in the aircraft industry. A typical case in this regard is the inspection of longitudinal contour templates of fuselage geometry. The efficiency of the method depends upon how well the contour data obtained from the inspection carried out on a CMM is matched and compared with the CAD data. This was first verified with fiducial data. As an example, the fuselage contour template of a typical aircraft model was taken for evaluation and was inspected at 500 points. The analysis of inspection for different densities of CAD point sets revealed a variation in inspection results clearly signifying the role played by the density of CAD point sets. This is indicated in Fig. 4.

With the accepted tolerance being 0.05 mm, the results indicate that even with 500 points obtained from the CAD data, the acceptance criterion is met.

In the case of a planar space curve, the deviation d between the inspection points and the nominal data points is obtained from the equation below.

$$d = \frac{\left|\left(\widehat{X}_2 - \widehat{X}_1\right) \times \left(\widehat{X}_1 - \widehat{X}_0\right)\right|}{\left|\left(\widehat{X}_2 - \widehat{X}_1\right)\right|} \tag{4}$$

where $\widehat{X}_1 = (x_1, y_1, z_1)$ and $\widehat{X}_2 = (x_2, y_2, z_2)$ represent the CAD points and $\widehat{X}_0 = (x_0, y_0, z_0)$ represent the inspection point.

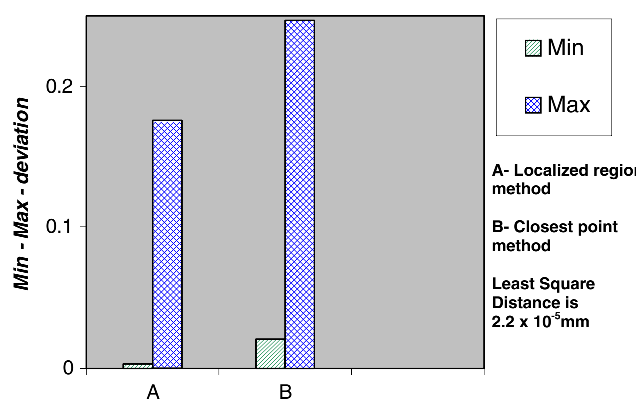


Fig. 6 Min–max error for various methods

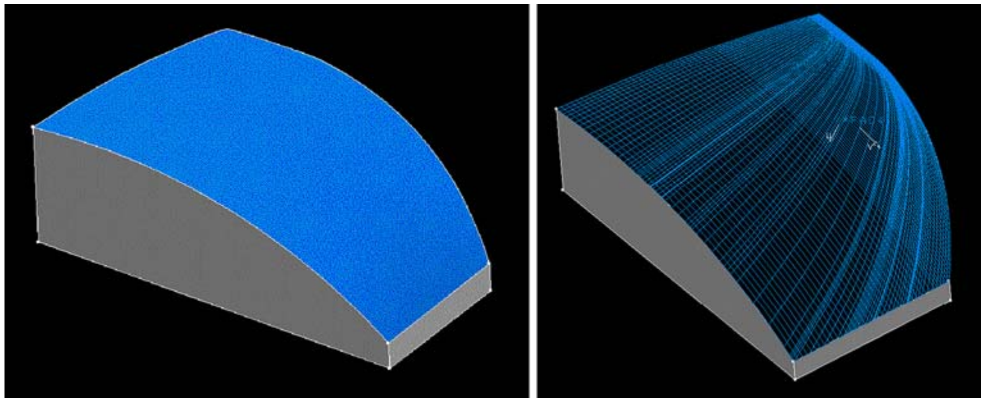


Fig. 7 Typical belly fairing form block tool

5.2 3D surface inspection

The component that is considered to carry out the 3D surface inspection is a complex surface with double curvature. Figure 7 shows typical form tools for the manufacturing of components with such shapes. The inspection of such form tools constitutes an important activity in the manufacture of a variety of components including, in particular, aircraft parts. The general manufacturing tolerance of such tools is ±0.25 mm.

The form tool that is considered here is of size 500× 250 mm. This surface is inspected at 1,100 points, and the nominal CAD data has 60,000 point sets. The inspection result obtained by the application of the modified ICP algorithm is shown in Fig. 8. The results indicate that the manufactured surface is well within the prescribed tolerance limits defined for 3D surface geometry and hence acceptable.

The second example considered is a machined component, viz., aircraft seat bracket, which is shown in Fig. 9, has multiple freeform surfaces. These surfaces were inspected across 100 points spread over both the surfaces shown as A and B in Fig. 9, while the part itself was represented by 200,000 CAD points. On implementation of the automated inspection methodology, the inspection results indicated that the maximum and minimum manufacturing deviations were 0.023 and 0.0004 mm, respectively. The results were further validated by inspecting the component that is located using hard registration (namely locating features in the part). Points on the component are measured by the CMM at each point where the proposed method computed the deviation. The deviation at each inspection point as computed by the localized region method and that obtained by inspection using hard registration is shown in Fig. 10.

This clearly indicates that the deviations obtained by the localized region method lies within the same band as that obtained from the hard registration technique. It is therefore feasible to use the proposed technique for soft registration in the automatic inspection of parts. Figure 6 shows a case where the use of other techniques in soft registration would result in accepting parts that are not within the acceptable tolerance band [16]. As the bar plot clearly shows, deviations obtained using the least squares technique indicate the part to be within tolerance, whereas the actual data and the localized region method both indicate the part to have much larger deviations. These comparisons show that the localized region-based measure for soft registration is robust, and the computed deviations are in close correspondence with the measurements obtained by inspection with hard registration.

A further study was conducted in a practical case to validate the use of the localized region based metric for computing the error. The component used earlier was inspected with the part position in a known reference frame [computed numerical controlled (CNC) machining reference frame, see Fig. 11]. For the part in this reference frame, the CMM is used to obtain points on the machined surface along pre-defined contours on the surface. The data thus obtained is registered with respect to the CAD model

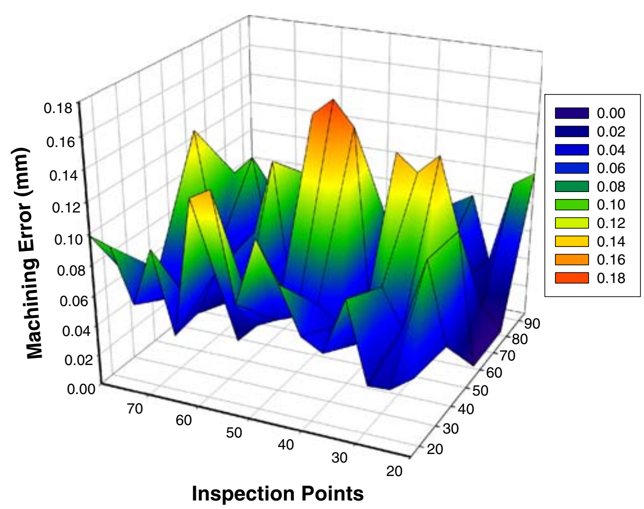


Fig. 8 Inspection results of modified ICP

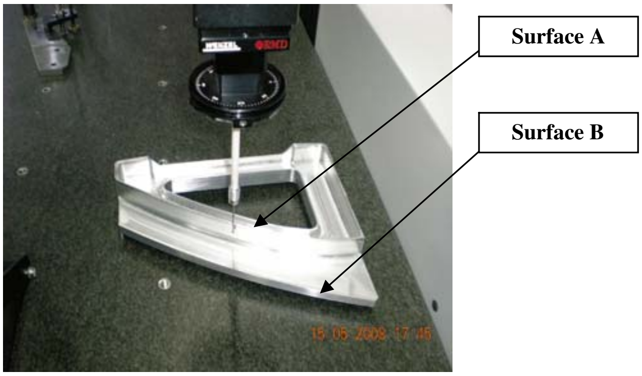


Fig. 9 Inspection of Aircraft seat bracket component on CMM

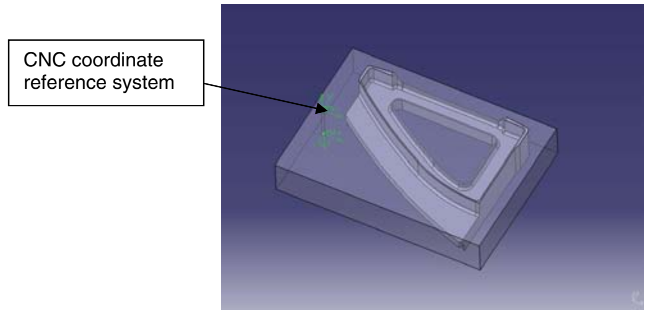


Fig. 11 Model of the seat bracket machined component with CNC coordinate reference system

data using the procedure outlined in this paper. In this position, the error between the registered inspection data and the nominal CAD surface is computed at the points along the contours. This error is then compared with the error obtained from the CMM data. As can be seen from Fig. 12, the error obtained in both the cases is in excellent agreement and falls within the same tolerance band. The maximum error shown by both the CMM and current inspection procedure is of the order of 30 µm, and the mean error by both the methods is of the order of 15 µm. This error is uniformly distributed around the mean approximately for the inspected set of points. As discussed above, the present approach is able to capture the error in the machined surface much better than other approaches in the literature.

6 Conclusion

This paper describes an efficient procedure to carry out automated inspection of space curves for templates and three-dimensional freeform surfaces. The procedure is essentially a modification of the traditional ICP to make it amenable to inspection of parts. The modification involves a new way to compute the deviation between the two datasets—measured and nominal. The localized region method proposed in this paper is better able to capture the deviations in the measured dataset as compared to the other techniques in use for comparing point datasets. The technique defines a local region by calculating the four topologically closest points for every inspection point to estimate the deviation of the measured point from the nominal surface. This allows a comparison to take place without accessing any of the CAD system utilities or data.

The computational time depends on the number of points in the datasets and the number of iterations carried out. When the point sets are small, computational time is largely dependent on the speed of convergence controlled by the predefined number of iterations.

This inspection procedure indicates that the implemented algorithm is accurate and fast to implement. This could be further fine tuned by establishing a good initial solution, and this forms the course of our future work. The retaining of the inspection data as points, even in situations where dimensions of a feature only are critical, needs to be examined.

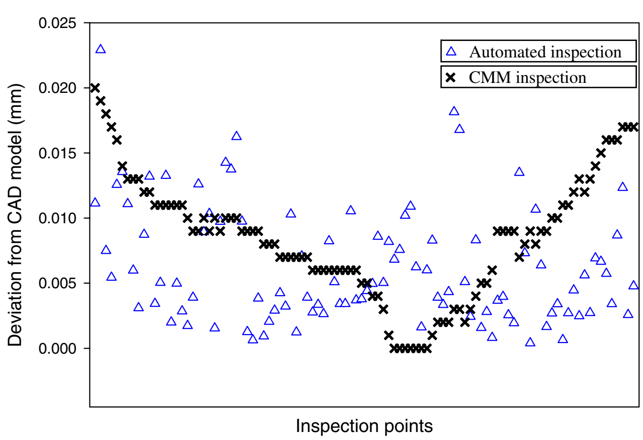


Fig. 10 Inspection results of seat bracket component

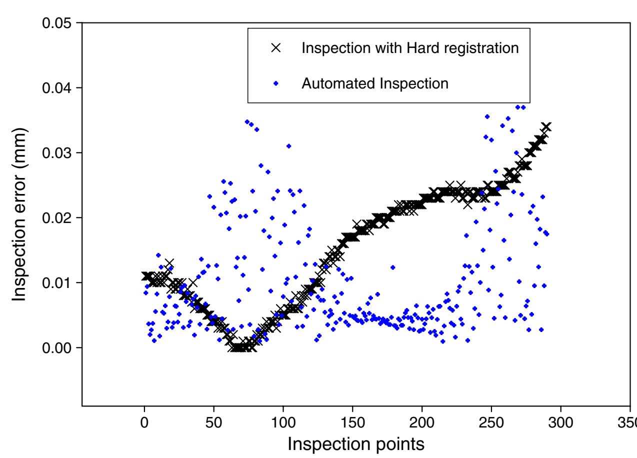


Fig. 12 Comparison of CMM vs automated inspection results for seat bracket component

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