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Improved the Performance of Iterative Closest Point Algorithm: Application to the Inspection of Freeform Surfaces

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Abstract

This study proposes methods to improve the performance of Iterative Closest Point (ICP) algorithm. This algorithm is used in many areas, such as the inspection of fabricated parts. The field of inspection is very necessary to ensure the quality of the production. The inspection of manufactured parts consists of automatically comparing their CAD model with their point clouds. The comparison of these two models makes it possible to conclude whether a manufactured part conforms to its theoretical model defined during its design. In this paper, the proposed control method is based on the ICP algorithm. The principle of this algorithm is to find the optimal rigid transformation to readjust the point clouds (measured on the real part) on the manufactured part. Many variants of ICP algorithm are proposed in this paper. They reduce errors and improve inspection, quality of machined parts. A comparison of their efficiencies on the purpose of improving performance and accelerating the convergence speed of the ICP algorithm is performed.

Keywords:
ICP algorithm, Quaternion, SVD, Freeform surfaces, Inspection.

1 Introduction

The three-dimensional (3D) inspection of parts is the comparison between the Computer Aided Design (CAD) model (theoretical model) of the part and the point cloud (real model) resulting from the acquisition (Mahmud et al. 2011). This comparison allows us to evaluate local and global errors that may exist between models and manufactured parts (Boughouas et al. 2008).

The method used is based on the Iterative Closest Point (ICP) algorithm (Besl and McKay 1992) (Chen and Medioni 1992), (Zhang 1994). This algorithm is widely used in various fields such as 3D reconstruction (Lu et al. 2006), simultaneous localization and mapping (Minguez et al. 2006), biometric recognition (Bowyer et al. 2006), medical image analysis (Almhdie et al. 2007), adaptation of machining paths (Azzam et al 2014) and 3D parts inspection (Biradar and Pande 2015). ICP algorithm is an iterative descent procedure to find the optimal rigid transformation between two models (for example, a point cloud and a CAD model).

The transformation is calculated to determine the rigid displacement that the measured surface (point cloud) would have to undergo to come to the nominal surface (CAD model).

This choice is justified by the robustness of this method, and it is important to underline here, that no attempt implementation in the software of the Coordinate Measuring Machine (CMM) has been reported in the literature relative on this research topic (Zhu et al. 2007).

This paper is organized as follows: in Section 2 describes the alignment process of the Iterative Closest Point (ICP) algorithm. The results and discussions of the application of the proposed approaches are presented in Section 3. This is followed by conclusions and future work in section 4.

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2 Alignment Process by ICP Algorithm

The ICP algorithm first introduced by Besl and McKay (1992) is a method for matching several types of geometric data such as point clouds, meshes and surfaces. The ICP algorithm is a well-known method for matching the set of 3D points to a model (Azzam et al. 2014). This algorithm is based on the minimization of the sum of the squares of the distances between the set of points (real object) and their correspondents belonging to the model (Besl and McKay 1992). Its goal is to find the optimal rigid transformation that will best match the point clouds (P) to a geometrical CAD model (M) (in this work, the CATIA V5 software was used) figure 1.

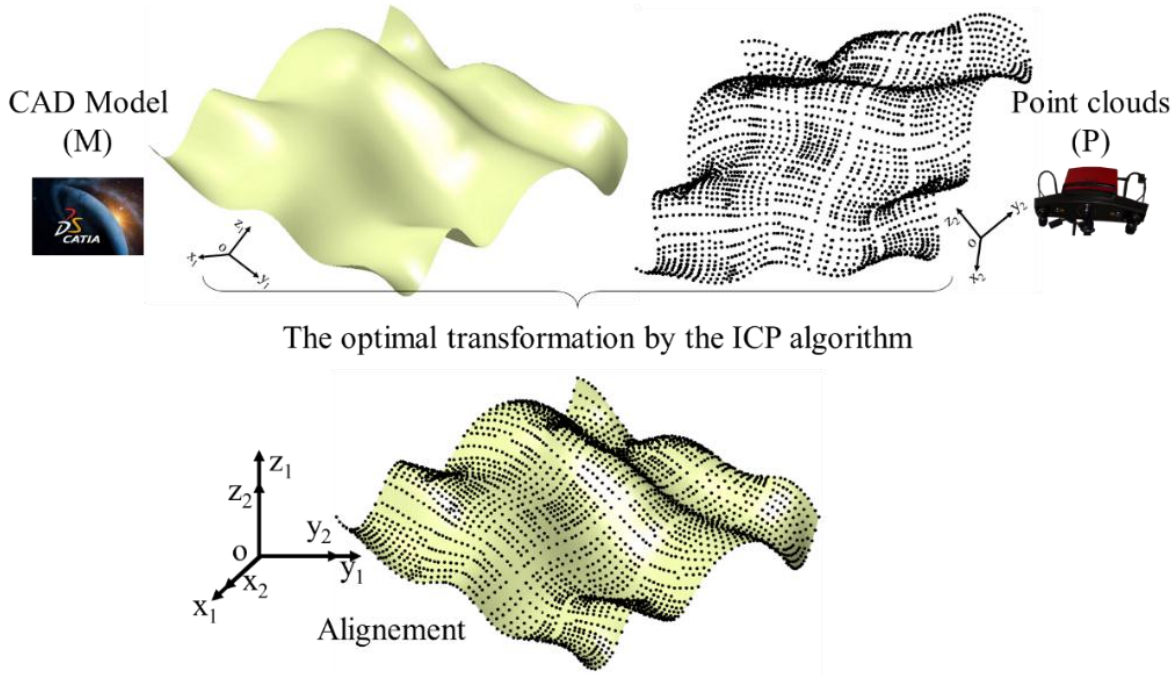

Figure 1. Matching a point cloud to a surface by ICP algorithm.

Figure 1 shows the method of matching a point cloud with a surface by the ICP algorithm. First, a CAD model (M) is realized by CATIA V5 software. The 3D scanning of the real surface is generally performed by non-contact measuring means, such as 3D cameras and scanners. From the measurements made on the manufactured part (real), a cloud of points of the surface is generated. The step of superimposing these two models (CAD model and point clouds) by calculating the rigid transformation (rotation + translation) is the so-called registration or matching.

The parameters of the rigid transformation i.e., the rotation and the translation (R, t) must minimize the cost function formulated by equation 1. This cost function is defined between the points P_i of the point cloud (P) and the points M_i belonging to the surface (M).

There are several methods for calculating the optimal rigid transformation between the two models such as Singular Value Decomposition (SVD) (Arun et al. 1987), unit quaternion (Horn 1987), orthonormal matrices (Horn et al. 1988) and dual quaternion (Walker et al. 1991).

$$E(R,t) = \sum_{i=1}^{N_m}\sum_{j=1}^{N_p} w_{i,j}\left\|M_i - (R.P_j + t)\right\|^2 \quad (1)$$

Where N_m and N_p, are the number of points in the model set M and point clouds P, respectively, and $w_{i,j}$ are the weights for a point match. The weights are assigned as follows: $w_{i,j} = 1$, if M_i, is the closest point to P_j, $w_{i,j} = 0$ otherwise.

The steps of the ICP algorithm can be summarized as follows (Azzam 2015):

1. Choose an initial transformation, to initialize the algorithm,

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2. Selection of points used.
3. For each point P_i of (P), search for the nearest point M_i in (M),
4. Calculate and apply the rigid transformation on point clouds (P),
5. Minimize the overall error between the two sets by miming the result of equation 1 in the least squares sense,
6. Repeat steps 2 to 5 until compliance with the convergence criterion.

Changes affecting one or more steps of the original algorithm have been defined to try to increase the performance of the ICP (Ezra et al. 2008). The performance indicators are essentially quantified by the final precision (Sun et al. 2016) and the speed of convergence (Du et al. 2016).

In this paper, the test of the improved ICP algorithm will be based on several variants:

- Selecting points in the dataset,
- Convergence speed of the algorithm,
- Minimization methods.

3 Results and discussions on the ICP Algorithm step

3.1 Selecting Points in the Dataset

There are several techniques have been proposed to select the points of the two models (P and M). In this work, a point selection technique based on the random draw of model points is proposed. This technique makes it possible to use samples of different points at each iteration. The number and the size of the samples are determined according to a probabilistic approach, to obtain at least a subset of pairs of points not containing mismatching. This will speed up calculations especially the Iterative Closest Point algorithm. As already mentioned before (see section 2), there are several techniques for calculating rigid transformation. In this case, the SVD method was used. The ICP algorithm is tested for percentages of different points each time, such as 10%, 50%, 80% and 100%, see figures 2 and 3.

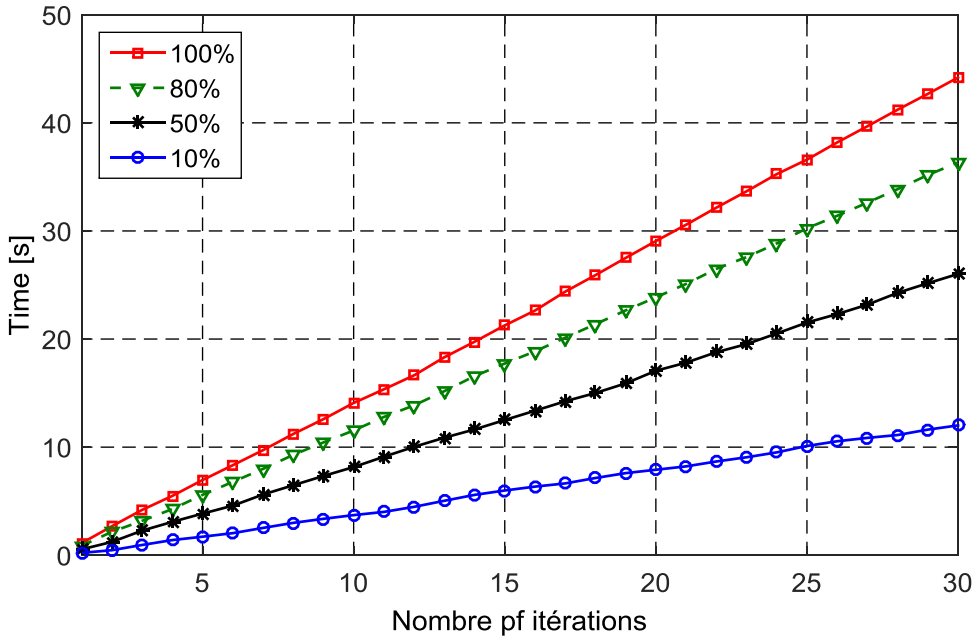

Figure 2. Comparison of the execution time (in seconds) of the algorithms on the freeform surface.

Figure 2 shows the convergence time of the Iterative Closest Point algorithm as a function of the number of iterations. This algorithm is uses a random draw solution of points with different percentages of points selection. This procedure reduces the size of the set of points that automatically reduces the convergence time (approximately 12 seconds for the random draw of 10% of the data). On the other hand, it is not guaranteed for the estimation of the optimal rigid transformation, as indicated in figure 3. The choice of the method is due to several factors, including

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the number of points (small or large data sets), with or without noise, the convergence stability of the models and the required accuracy.

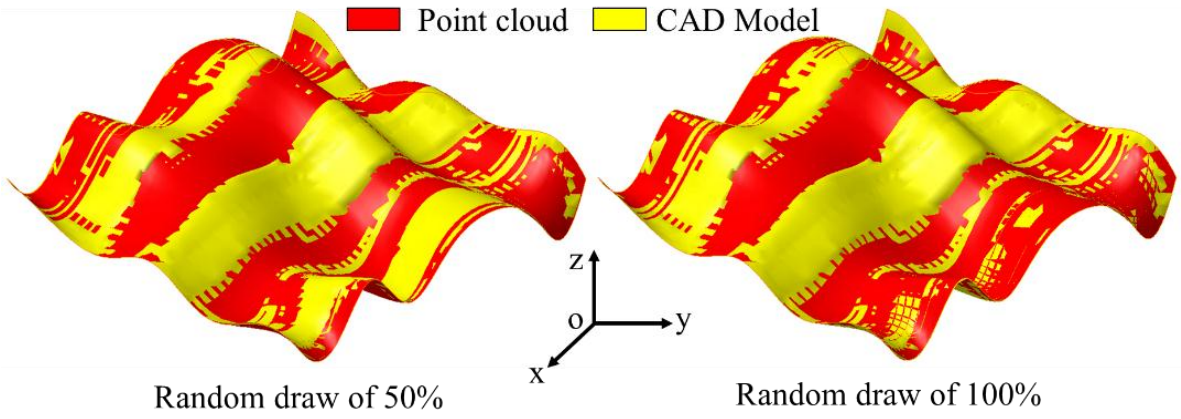

Figure 3. Comparison the random draw solution

Figure 3 illustrates a comparison of the point selection solution between random draw of 50% and 100% of the data. This figure shows the mapping of the gaps between the CAD model and the real model (point clouds) for both cases (50% and 100%). The registration results are used to check the dimensional and geometric tolerances of the parts. It is noted here that the red color represents the CAD model while the yellow color represents the real model. As a result, we observed a significant reduction in deviations (gaps between the CAD model and the point cloud) with the use of 100% random draw compared to that obtained by the random draw of 50% of the data.

The following section presents proposed convergence methods for accelerating the ICP algorithm.

3.2 Convergence Speed of the Algorithm

On the other hand, to speed up the basic ICP algorithm, many methods have been used. Fitzgibbon (2003) used the Levenberg-Marquardt algorithm to accelerate ICP. In contrast, Jost and Hugli (2002), Kim and Kim (2010) presented a comparison of existing methods to accelerate the ICP algorithm and proposed and analyzed a new, fast ICP algorithm for registration. Also in this case, the SVD method was used. In this research work, the proposed method is Delaunay triangulation. This method makes it possible to go from a point cloud to an STL model, see figure 4.

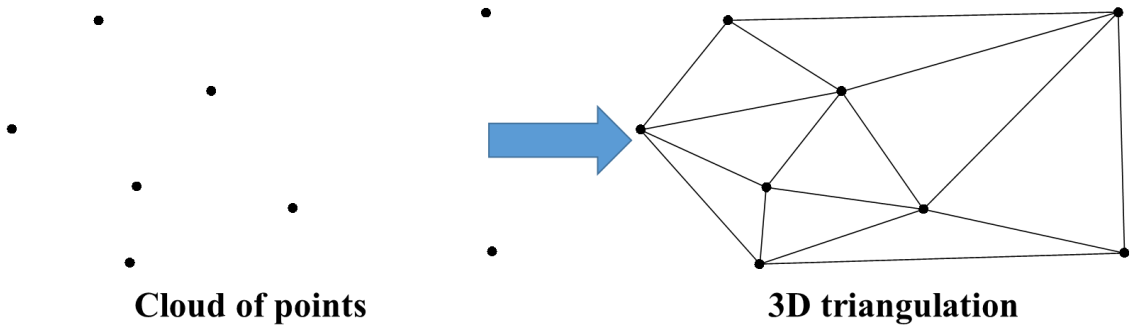

Figure 4. Delaunay triangulation method.

Figure 5 shows the variation of the execution time as a function of the number of iterations of the two algorithms (basic ICP and improved ICP). Note that the execution time varies linearly in both cases. Thus, this figure shows that the improved ICP algorithm that uses the Delaunay triangulation method is faster (the time of convergence is approximately 4 seconds) than the basic ICP algorithm (the time of convergence is approximately 83 seconds).

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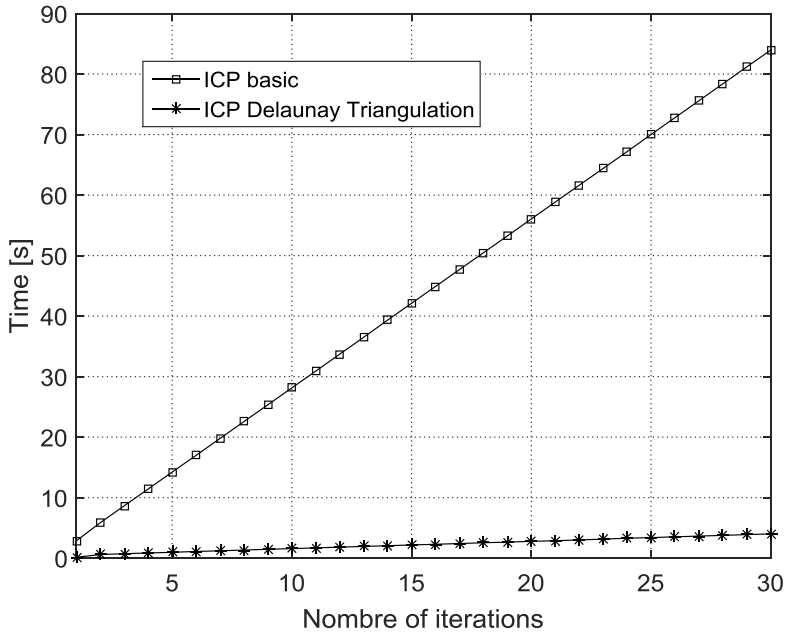

Figure 5. Comparison of convergence time for a variety of matching algorithms.

The following section presents the proposed minimization methods for the ICP algorithm.

3.3 Minimization Methods

The principle of the ICP algorithm is to find the rigid transformation [rotation + translation] for the alignment of the point clouds on the CAD surface. In this part, four non-linear optimization methods of the improved ICP algorithm are proposed, such as Singular Value Decomposition (SVD) (Arun et al. 1987), Unit Quaternion (UQ) (Horn 1987), Dual Quaternion (Walker et al. 1991) and structures such as kd-tree (Greenspan and Yurick 2003). The results are shown in figure 6.

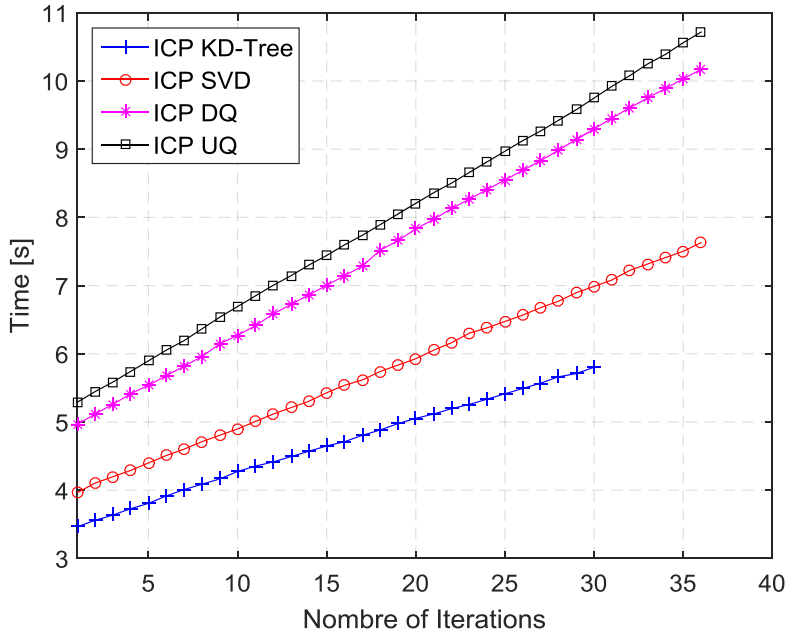

Figure 6. Execution time according to the number of iterations.

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Figure 6 shows the execution time in seconds of the four-optimization methods of the ICP algorithm (kd-tree ICP, ICP SVD, ICP DQ, and ICP UQ) as a function of the number of iterations. This figure shows that the final value of the execution time after alignment is lower than with the kd-tree method: T(ICP kd-Tree) = 5.80s, T(ICP SVD) = 7.62s, T(ICP DQ) = 10.17s and T(ICP UQ) = 10.71s.

On the other hand, this figure clearly shows that the kd-tree method converges rapidly to a stable solution after a maximum of 30 iterations, whereas the other methods such as SVD, quaternion dual (DQ) and unit quaternion (UQ) converge after 36 iterations.

4 Conclusion

This paper, presents methods for improving the performance of Iterative Closest Point (ICP) algorithm to inspect freeform surfaces. This algorithm is used in many fields, such as machining, biomechanics and the inspection of fabricated parts.

The main purpose of the ICP algorithm is to find the optimal rigid body displacement between two sets of data. This alignment algorithm allows recalibrating the measured surface (point clouds) on the CAD model (theoretical model).

Subsequently, approaches to improve the performance of the ICP algorithm are proposed. A first test allowed to test the selection of the points of the two models. It allowed us to show and validate that the point selection method was effective. In addition, the proposed method makes it possible to accelerate the ICP algorithm significantly. On the other hand, it is not guaranteed for the estimation of the optimal rigid transformation.

The second test concerns the convergence speed of the ICP algorithm. His test is compared both basic and improved algorithms. It allowed us to show that the Delaunay triangulation method is faster than the basic method, which is logical because the number of points has been reduced.

The third test realized also improves the performance of the ICP algorithm, but also to highlight the effect of the minimization techniques used in the ICP algorithm. The test clearly shows that the kd-tree method is the most efficient towards a stable and fast solution.

The inspection method used is based on the ICP algorithm. When there is a lot of measurement noise in the point cloud, the ICP converges to a false minimum. In future works, new ways could be explored to limit this noise.

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Biographies

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