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Differential evolution algorithm-based range image registration for free-form surface parts quality inspection

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ABSTRACT

Increasing demands on precision manufacturing of complex free-form surface parts have been observed in the past several years. Although some advanced techniques have been employed to solve the design and machining problems for such parts, quality inspection remains a difficult problem. Registration is a crucial issue in surface inspection; it is used to transform the design model and measurement model into a common coordinate system. The comparison results are then outputted in a report and displayed visually by color gradients. This paper presents a design model-based inspection method with range image registration, in which the measurement model is represented by a series of 3D discrete points. In the model preprocessing, the directed Hausdorff distance (DHD) method is employed for point cloud simplification, and a novel point descriptor is designed to evaluate the property of each point. Subsequently, a differential evolution (DE) algorithm-based optimizer is proposed for error evaluation. Combined with the properties of 3D points, the optimizer can measure the similarity between the design model and the measurement model with a recursive process. The proposed algorithms have been implemented and tested with several sets of simulated and real data. The experiment results illustrate that they are effective and efficient for free-form surface part quality inspection.

1. Introduction

Free-form surface parts have been widely used in aerospace, shipbuilding, and automobile manufacturing. In these fields, a high degree of precision is required for the dimensional inspection of parts with complex surfaces. Because the free-form surface parts have abundant geometric details and complex topologies, the tolerance specifications become the critical link between the designer and the manufacturer. In general, the tolerance is a specification that defines the acceptable variation of the dimension or geometry of an element. In the past few decades, a traditional coordinate measurement machine (CMM) has been widely used for quality inspection in terms of sampling the 3D points with probe. However, the contact process may produce extra errors for mutability parts [1]. Additionally, the complex concave structure of the parts limits the path of the probe during inspection, and thus, some key points cannot be obtained effectively. Moreover, the sampling of CMM with the probe is inefficient [2]. Recently, under ever-increasing demands on improving product quality and reducing the production cycle time, the non-contact measurement technique is a popular option for quality inspection [3,4]. Non-contact measurement is conducted based on the design model, i.e., a computer aided design (CAD) model. In the process, the machined part is scanned first to generate the measurement (scanning) model with a large number of 3D points. Assuming that the CAD model is fixed, the measurement model is transformed to align to the CAD model. Finally, the quality errors of the part are displayed for the non-aligned regions. In this paper, we are mainly concerned about the profile tolerance of free-form surface parts for quality inspection. It should be noted that the design and measurement models are located in the design coordinate system (DCS) and measurement coordinate system (MCS), respectively, and the relationship between the DCS and MCS is complex. Therefore, an optimal transformation matrix is needed to conduct the transformation, and this process is referred to as range image registration [5]. Because the initial position of two models are unknown, the accuracy and efficiency of the manual registration are relatively low and cannot meet the strict precision criteria. In this paper, for free-form surface parts quality inspection, we mainly focus on searching for the global optimal transformation matrix to register the CAD model and the measurement model automatically.

Registration is a challenging and well-known NP-hard problem within the computer vision field [6]; it has numerous applications such as in 3D reconstruction, object recognition, virtual museums, and in

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the medical fields [7–9]. The objective of registration is to match two models as closely as possible in a common coordinate system. As for quality inspection, ideally, each point of the measurement model should find the current corresponding point in the design model. However, in practical applications because the size of the two models are different and the initial position is unknown, the successful correspondences are difficult to obtain. The incorrect estimation of the corresponding points may yield a misleading measurement. The high symmetric and more planar structure make the problem more difficult. In this area, the iterative closest point (ICP) [10] is the best known method to compute the transformation matrix based on the singular value decomposition (SVD) or quaternion methods. However, ICP is sensitive to the initial position, noise, and outliers. A good initial guess is essential to finding the correct solution for ICP; that is, when two models are far from each other the ICP is easily trapped in local minima [11,12]. Bergström et al. [13] introduced a modified version of the ICP algorithm where the iteratively re-weighed least squares (IRLS) was employed to incorporate the robustness. Without the ICP method, Li et al. [14] proposed a point-based registration algorithm with adaptive distance function (ADF), which applied the Levenberg-Marquardt (L-M) optimization algorithm to calculate the non-linear least-squares problem. Although there are numbers of simple variant of ICP methods, certain aspects of the registration process still need to be tested further in real application situations. In the past few years, many types of heuristic algorithms were introduced to solve the complex optimization problem, such as the improved genetic algorithm (GA), particle swarm optimization (PSO) algorithm, and artificial bee colony (ABC) algorithm [15,16]. For free-form surface parts quality inspection, He et al. [17] proposed a profile error evaluation algorithm that combined the differential evolution (DE) algorithm and the Nelder-Mead (NM) algorithm. The classic DE algorithm [18] is a simple yet effective approach; however, when used for the complex registration problem, the basic DE algorithm cannot guarantee that the achieved results were globally optimal solutions. Luck et al. [19] used a simulated annealing (SA) algorithm with ICP to solve the registration problem, in which the SA was used to jump out the local optimal and the ICP was employed to accelerate the searching. Chow et al. [20] introduced a dynamic GA to register two models for 3D modeling. Cordon et al. [6] used the scatter search (SS) and harmony search (HS) algorithms to register different models; in addition, they extended the registration method to solve a medical problem [21]. Falco et al. [22] proposed a software system grounded on the DE algorithm to automatically register multi-view satellite images with maximization of the mutual information. Yang et al. [23] employed the cat swarm optimization (CSO) algorithm for non-rigid multi-modal image registration using the normalized mutual information measure model. With their good search capabilities, heuristic algorithms can find the optimal transformation matrix throughout the search space, and they are becoming powerful methods for solving registration problems. However, in practical terms, the measurement model contains millions of points, and a stochastic search of the heuristic algorithms is time-consuming.

To improve the efficiency, some simplification methods are employed for registration. Note that, with respect to the effectiveness, the feature and the boundary regions of the model should be maintained during simplification. In some papers, clustering and iterative simplification methods are introduced with polygonal meshes or splines [24,25]. However, these methods are computationally involved and require substantial amounts of main memory. Most frequently, surface fitting is applied to estimate the surface features; specifically, the normal and curvature information is constructed to assist the process because they are important visual cues for shape perception. Li et al. [26] presented a systematic introduction of the blade optical inspection, and the improved hierarchical clustering method was used to accelerate the computation of quality inspection. Rusinkiewicz et al. [27] introduced the concept of a normal space-directed sampling method, in which points are chosen such that the distribution of normal points among the selected points is as large as possible. To reduce the complexity of 3D objects, Diez et al. [28] proposed a hierarchical normal space sampling method that relied on normal sampling and distance restrictions. Shi et al. [29] presented an adaptive simplification method to reduce the number of scanned dense points with a *k*-means clustering algorithm, and an automatic recursive subdivision scheme was designed. Álvarez et al. [30] used an evolutionary multi-objective algorithm to solve the mesh simplification problem. During this process, two conflicting objectives – the accuracy and the simplicity – were considered simultaneously. As mentioned above, these methods can be adopted to achieve a reduced and characteristic subset of the original point sets. However, the latter procedure usually needs the intervention of expert users to obtain high-quality features. In addition, the complexity of these methods is relatively high when used for registration. To balance the accuracy and efficiency, Chow et al. [20] chose 300 points randomly from the input models for registration. Santamariá et al. [31] used a uniform distribution sampling method to accelerate the computation of the objective function. However, for quality inspection, these simplification methods may lose some feature and boundary information, and the computed errors are unreliable. Furthermore, the sampling irregularity may lead to incorrect clustering results.

To improve the accuracy of the registration, the salient structure, i.e., features, are extracted in the models [32–34]. The key requirement of feature-based registration is the establishment of reliable correspondence between the two sets of feature points. In some papers, the features are only used for pre-registration (coarse registration) [35], which is an independent step of fine registration and does not fully use the advantage of the features. In a practical application, the geometries of the models are different and the initial positions are complex, therefore, we require the feature space to be invariant to the 3D rotations and translations, as well as insensitive to the point cloud density and noise to a certain degree. In a quality inspection, the measurement error and quantization error is inevitable, and the correspondence directly influences the quality of the inspection. Therefore, we need to detect a certain number of key points that are prominent according to a specific criterion. Rusu et al. [36] proposed persistent feature histograms (PFH) to match the point clouds from different views, in which each point was estimated by 16D features based on the normal. Guo et al. [37] presented rotational projection statistics (RoPS) for the local feature description of a point set. Yang et al. [38] proposed a local feature statistics histogram (LFSH) for registration, in which the local depth, point density, and normal were encoded to describe the local shape geometries. In these methods, several criteria exist to decide which points should be kept and which points should be discarded. In general, the point descriptor has been widely used in coarse registration to provide initial solutions for fine registration, which is an iterative and independent process to coarse registration. Therefore, the initial solutions from the feature estimation are underutilized.

The DE algorithm is a simple and efficient method and has been used in a number of areas [39–43]. Recently, in a time series classification, a number of neural network studies has been published with the DE algorithm for parameter optimization [44–46]. In the past few decades, a variety of enhanced DE algorithms have been proposed such as JADE [47], EPSDE [48], SBDE [49], IDE [50], etc.; the effectiveness of these algorithms is illustrated for function optimization problems. Additionally, the self-adaptation mechanism has often been combined with DE popularly [51]. However, regarding quality inspection, the algorithm need to be redesigned according to the specific problem. In this paper, we combine the DE-based optimizer with point cloud preprocessing methods to register the CAD model and measurement model for quality inspection. To solve the quality inspection problem with range image registration, the proposed pipeline is shown in Fig. 1. First, the practical manufactured part is scanned in terms of

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