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An automatic and robust point cloud registration framework based on view-invariant local feature descriptors and transformation consistency verification

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ABSTRACT

This paper presents an automatic and robust framework for simultaneously registering pairwise point clouds and identifying the correctness of registration results. Given two partially overlapping point clouds with arbitrary initial positions, a view-invariant local feature descriptor is utilized to build sparse correspondence. A geometry constraint sample consensus (GC-SAC) algorithm is proposed to prune correspondence outliers and obtain an optimal 3D transformation hypothesis. Furthermore, by measuring the similarity between the estimated local and global transformations, a transformation consistency verification method is presented to efficiently detect potential registration failures. Our method provides reliable registration correctness verification even when two point clouds are only roughly registered. Experimental results demonstrate that our framework exhibits high levels of effectiveness and robustness for automatic registration.

1. Introduction

3D point cloud registration is a vital process for integrating multiple partial point clouds into a complete 3D model, and has been widely used in many 3D scanning systems [1–6]. In these 3D scanning systems, the prevailing registration methods rely on artificial markers attached to the measured surfaces, or on tracking the pose of the 3D sensors [1]. However, in many applications such as robot navigation, remote sensing, cultural artifacts protection, and large-scale surface modeling, attaching marks is often not allowed, and usage of external locating devices is inconvenient.

In recent years, automatic 3D registration methods have been extensively researched because they do not require manual intervention or external assistance [7–15]. Given two partially overlapping point clouds with arbitrary initial positions, automatic 3D registration methods can estimate an optimal rigid transformation that best aligns the point clouds [8,13]. Available automatic point cloud registration methods [9–14] typically consist of coarse and fine registration steps. The coarse registration step obtains an approximate initial transformation [14,16,17], which will be further refined by the subsequent fine registration step using the iterative closest point (ICP) algorithm [18] and its variants [19,20]. In general, coarse registration utilizes 3D local feature descriptors to build sparse correspondence, and such 3D local feature descriptors are often defined in a transformation-invariant manner. A number of 3D local feature descriptors have been proposed to encode the geometric information of a local surface into high-dimensional features [21]. Johnson and Hebert [22] proposed a spin image by spinning a plane around the normal and computing the number of points falling into the image bins. Similarly, Chen and Bhanu [23] proposed a local surface patch (LSP) by integrating normal angles and curvature-based quantities into a 2D histogram. Both of these methods use the point-normal as the local reference axis (LRA), while the descriptiveness of LRA-based local feature descriptors is greatly limited because only the surface normal is used as a reference; there is a gauge of freedom in the rotation around the axes that must be eliminated [16]. Based on this consideration, many local reference frame (LRF)-based local feature descriptors have been proposed to enhance their descriptiveness [12,16,17,24]. In these proposed descriptors, the LRF is usually constructed using Eigen analysis of the neighbor points in a spherical support. Using sets of local features extracted for each point cloud, point correspondences are established by comparing the similarity of local features. However, mismatches (outliers) may widely exist owing to various nuisances, including sensor noise, partial overlap, varying point resolution, and similar local surface shapes [21]. The existence of mismatches usually makes traditional transform estimation methods (such as least squares estimators) inapplicable. In this case, robust estimators must be applied to obtain reliable point correspondences [25].

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During the past few decades, various estimators have been proposed for robust transform estimation; for example, RANSAC [26] and MLESAC [27] are two widely used estimators. They both use resampling to obtain an outlier-free subset to estimate a reliable and rigid transformation. The difference is that MLESAC chooses the solution that maximizes the likelihood rather than the inlier count; RANSAC does the opposite. These methods work well when the outlier ratio is small, but they tend to degrade severely if the proportion of outliers is large; the resampling efficiency is affected strongly by the outlier ratios. Thus, additional feature searching constraints must be employed to prune the vast search space, and facilitate feature correspondence searching. Moreover, in many real-world registration tasks, it is common to have two sequential point clouds with very small or even no overlap regions, which can result in a very large fraction of outliers in the point correspondences set. To the best of our knowledge, no existing estimator can guarantee an outlier-free subset when the percentage of outliers is greater than 90% [28], which will inevitably lead to false coarse registration results. False registration results without prompt detection will further result in shape artifacts in the final models. As a result, verifying the correctness of coarse registration results is vital for a robust point cloud registration process.

Existing registration correctness verification methods are typically based on local surface consistency principles [9,11,14]. The local surface consistency is a measure of the degree to which the overlap regions of two registered point clouds can represent the same object surface. Specifically, local surface consistency can be measured by calculating the overlap distance or checking the visibility consistency between the registered point clouds. The former directly calculates the average distance between the surfaces in overlap regions [9,14], and the latter checks the visibility consistency of two surfaces along the line of sight from each viewpoint [11,14]. In these two methods, the point clouds must first be closely registered; thus, they can only be used for verifying the correctness of fine registration results. However, if a false coarse registration result is used as the initial pose, the fine registration step will inevitably fail. The ICP iteration process greatly increases computation costs, especially when the point cloud size is very large.

According to the above analysis, the key to automatic and robust 3D point cloud registration lies in integrating robust coarse registration with effective registration correctness verification. Prior work [10,12,17,25] focused more on improving the performance of coarse registration algorithms, while neglecting the importance of registration correctness verification. In existing automatic registration methods, pairwise point clouds are first registered together, and a global model is constructed based on the pairwise registration results. A critical weakness of such pipelines that we addressed is the low precision of coarse registration results. Owing to various nuisances, coarse registration algorithms are error-prone, which leads to shape artifacts in the final models. Actually, registration correctness verification has been proven to be extremely important for a practical automatic point cloud registration system [9]. In this work, we present a robust 3D point cloud registration framework for automatically registering pairwise point clouds and identifying the correctness of coarse registration results. The framework brings pairwise point clouds into rough alignment without the need for assumptions about the initial positions and overlap information. Then, to classify coarse registration results as either correct or incorrect, they are directly checked with a novel registration failure detection method. Coarse registrations verified as correct are taken as the initialization to the ICP variants for further iterative refinements. Based on the fine registration results, an accurate global model can finally be constructed.

The main advantages of our framework can be embodied by the following two aspects. First, a view-invariant local feature descriptor with both high descriptiveness and strong robustness is used for building sparse correspondence; a robust transform estimation algorithm, referred to as GC-SAC (geometry constraint sample consensus), is also proposed to remove correspondence outliers and estimate a reliable 3D transformation. The algorithm utilizes the rigidity of a point cloud surface as the geometry constraint to (1) obtain a group of distance-compatible feature correspondences, (2) ensure that the resampling efficiency is not affected by the outlier ratios, and (3) speed up the transformation hypothesis generation process. Second, we present a novel registration failure detection method based on the transformation consistency principle. Compared with prior local surface consistency-based methods, our method can provide reliable verification of registration correctness, even when two point clouds are only roughly registered together; this greatly reduces total computation costs.

2. Robust pairwise registration using view-invariant local feature descriptor

In this section, we describe the process for robustly registering pairwise point clouds using view-invariant local feature descriptors.

2.1. Keypoints detection

The solution to the coarse registration problem lies in finding correct point correspondences between pairwise point clouds. However, for each pre-registered point cloud, which may contain millions of points in some instances, it is impractical to establish one-to-one correspondence for each point inside; the 3D local feature extraction and matching process will greatly increase computation time. Furthermore, the surrounding 3D geometric shapes between any two neighbor points do not differ significantly; their computed local features are generally very similar. Thus, it is essential to detect a limited number of keypoints that can effectively describe the point cloud surfaces.

Many keypoint detection methods have been proposed for 3D recognition applications [29]. While they mostly focus on distinctiveness, only a small number of keypoints can be detected, and those detected keypoints spread only in convex or concave areas. In comparison, in the coarse registration problem the overlap regions are not known until two point clouds are registered together. Therefore, it is vital for the detected keypoints to spread uniformly over the entire point cloud surface; this prevents random bias in the feature matching steps. In this study, we adopt the shape index measure [23] to detect the keypoints. For a point p_i in point cloud P, its shape index is defined as:

$$SI(p_i) = \frac{1}{2} - \frac{1}{\pi} tan^{-1} \frac{k_1(p_i) + k_2(p_i)}{k_1(p_i) - k_2(p_i)} \tag{1}$$

where $k_1(p_i)$ and $k_2(p_i)$ are, respectively, the maximum and minimum principal curvatures of point p_i. With this definition, all local region shapes can be mapped into the interval [0, 1]. Point p_i is detected as the keypoint only when its shape index $SI(p_i)$ satisfies one of the following two conditions:

$$SI(p_i) \geq \max_{q \in N(p_i)} SI(q) \text{ and } SI(p_i) \geq (1+\alpha)\mu(p_i) \tag{2}$$

$$SI(p_i) \leq \min_{q \in N(p_i)} SI(q) \text{ and } SI(p_i) \leq (1-\beta)\mu(p_i) \tag{3}$$

where

$$\mu(p_i) = \frac{1}{N_i} \sum_{q \in N(p_i)} SI(q) \tag{4}$$

$N(p_i)$ is the points in the neighbor area of point p_i, N_i is the total number of points in $N(p_i)$, $\mu(p_i)$ is the average shape index value within the neighbor area of p_i, and α and β are two scalar factors that determine the final keypoint amounts. Detected keypoints lying in the boundaries will be excluded to avoid systematic bias in the constructed LRFs (Section 2.2).

Fig. 1 shows the keypoint detection results of two point clouds from model *Dragon*, in which the detected keypoints are represented with red points and the point clouds are transformed into 3D meshes for better visualization. Our detected keypoints are concentrated in highly protruded and highly curved areas; these keypoints spread quite uniformly over the entire surface, and only highly planar areas are filtered so as