Optics & Laser Technology 46 (2013) 53–60

Contents lists available at SciVerse ScienceDirect

Optics & Laser Technology

journal homepage: www.elsevier.com/locate/optlastec

An automatic registration algorithm for the scattered point clouds based on the curvature feature

Bingwei He [a,*], Zeming Lin [a], Y.F. Li [b]

[a] School of Mechanical Engineering and Automation, Fuzhou University, Fuzhou, PR China
[b] Department of Mechanical and Biomedical Engineering, City University of Hong Kong, China

ARTICLE INFO

Article history:
Received 25 April 2011
Received in revised form
28 March 2012
Accepted 20 April 2012
Available online 23 May 2012

Keywords:
Registration
Curvature
Circumference feature

ABSTRACT

Object modeling by the registration of multiple range images has important applications in reverse engineering and computer vision. In order to register multi-view scattered point clouds, a novel curvature-based automatic registration algorithm is proposed in this paper, which can solve the registration problem with partial overlapping point clouds. For two sets of scattered point clouds, the curvature of each point is estimated by using the quadratic surface fitting method. The feature points that have the maximum local curvature variations are then extracted. The initial matching points are acquired by computing the Hausdorff distance of curvature, and then the circumference shape feature of the local surface is used to obtain the accurate matching points from the initial matching points. Finally, the rotation and translation matrix are estimated by the quaternion, and an iterative algorithm is used to improve the registration accuracy. Experimental results show that the algorithm is effective.

1. Introduction

To reconstruct 3D models of objects quickly and accurately is one of the crucial tasks for computer vision. The first step in the modeling process is the data capture with the three-dimensional optical measuring equipment, which can effectively obtain three-dimensional surface point data of object surface. Due to the limit of measuring range and the line property of the optical transmission, a number of range images from different viewpoints have to be captured and combined to obtain the entire object surface. This stage is called the data registration. The registration of multiple range images is a crucial step in 3D computer vision and its goal is to find out the relative position and orientation of one data set to the other data sets.

1.1. Previous work

The traditional registration method is to glue labels on the measured object, or use a rotary table which has a high-precision [1]. Although two methods are relatively simple, they cannot get the information on the bottom of object, and the glue label would block the surface orientation and high-precision rotary table for the operators with high technical requirements. Besl and McKay [2] proposed the ICP (Iterative Closest Point) algorithm which through constant searches the closest points between two point sets to establish the corresponding relationship. However, ICP requires a data set is a subset of another data set, and requires the good initial position estimation. ICP needs to search the closest points between two point sets at each iterative step, but the searching process is time-consuming and would monotonically converge to the local minimum. Chen and Medioni [3] used the distance of two normal vectors as the evaluation function, instead of the distance between points, but this method requires solving the nonlinear least squares problem, so the computation is not effective, and it also needs the two objects close enough. Masuda and Yokoya [4] introduced the least median of squares estimator to reduce the outlier effects, but it requires re-sampling in per iteration. Park and Subbarao [5] proposed the CCP (Contrastive Projection Point) algorithm, but still cannot solve the complex multi-view positioning issue. Moreover, later people came forward with many advanced algorithm base on ICP method [6–8].

In the last decade, many registration algorithms based on the geometric features such as hole, edge, corner, normal, were proposed. Jiang et al. [9] introduced an angular-invariant feature for the registration procedure, to perform a reliable selection of corresponding points. The feature is a k-dimensional vector, and each element within the vector is an angle between the normal vector and one of its k nearest neighbors. The angular feature is invariant to the scaling and rotation transformation, and is applicable to the surface with a small curvature. A vector-based method of automatic point cloud registration algorithm is proposed by Makadie et al. [10]. The algorithm calculated the normal

* Corresponding author.
E-mail address: bingwei_he@hotmail.com (B. He).

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http://dx.doi.org/10.1016/j.optlastec.2012.04.027

vector of each point, and then compared the normal histogram to find the corresponding sets and rough register the data sets. The intensive registration is completed by ICP algorithm finally. Oztireli and Basdogan [11] developed a K-neural network algorithm to search the characteristics of surfaces, but it is time-consuming. Curvature is a good invariant feature of local surfaces, and is gradually used in the three-dimensional registration technology. Chen and Bhanu [12] analyzed the curvature distribution on local surfaces, and established a two-dimensional histogram of the surface type and angle, and the local surface characteristic consisted of the histogram, surface type and the center of gravity. Zhu et al. [13] presented a hash registration algorithm base on the curvature and normal vector. In this algorithm, all pair-wise points located are whose curvatures are sufficiently similar, and all the rigid transformations that map the first point to the second one are computed, while making the normal vectors coincide. A hash table is constituted from the coordinate transformations in the 3D space to find the perfect registration. Lu et al. [14] proposed to calculate the Hausdorff distance of curvature, by comparing the Hausdorff distance to find correspondence sets. The method required the point clouds for registration to be with the same structure. Devrim [15] accounted that it cannot be a precise matching using the curvature only, and other information like intensity, color, texture, should be included. However, this information has high requirements for the measurement equipment. Jakub and Jan [16] described a two-dimensional image registration method developed from the CPCM (Cylindrical Phase Correlation Method) algorithm, and it will convert the information in the 3D space into cylindrical coordinates. But the CPCM is reused to seek the transformation relation based on a polar coordinate domain characteristic, and this method needs a pair of three-dimensional images with a known shaft. Faysal and Muharrem [17] defined the local neighborhood as an energy function, and the minimum at the energy function represents the convex in the neighborhood. The algorithm needs to do the Gaussian transformation and easily falls into a local maximum. At present, the initial alignments in some algorithm are achieved manually or by the use of characteristic markers in the scene. Sometimes, some algorithms easily fall into a local maximum when the initial alignment is not good. Therefore, it is important to know how to register 3D point clouds automatically with partial overlapping and without any manual rough alignment or the use of landmarks.

1.2. Our work

In this paper, a novel curvature-based point cloud registration method was presented (shown in Fig. 1).The method could automatically register without manual operation, and the initial position of two point clouds can be in any place.

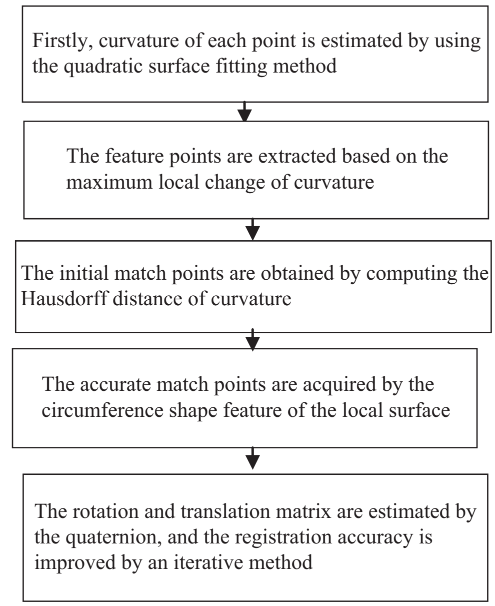

Fig. 1. Workflow diagram of our proposed method.

2. Automatic registration method based on the curvature feature

2.1. Calculating the normal vector of the point

Let p_i denote the ith measured point of the point set $P=\{p_1,p_2,p_3,\ldots,p_n\}$. K nearest neighbors of point p_i is defined as the points which are K nearest to point p_i, noted as $N\ bhd(p_i)$.

The normal vector at any point in point clouds is equivalent to the normal vector of the tangent plane of the surface, which is constructed with the point and its K nearest neighbors. According to the point p_i and its K nearest neighbors, the covariance matrix N is constructed:

$$N=\sum_{q_i\in N\ bhd(p_i)}(q_j=\overline{p}_i)(q_j-\overline{p}_i)^T \tag{1}$$

where $\overline{p}_i$ is the centroid of $N\ bhd(p_i)$. The eigenvector $\xi_{\min}$ corresponding to the minimum eigenvalue $\lambda_{\min}$ of matrix N is the normal vector n_i of the tangent plane [18].

Since the orientations of the normal vector vary, an adjustment method must be implemented to make all normal vectors forward to the same side of the surface. Hoppe et al. [19] proposed a method that is based on the "transmission" ideology which is used in this paper. Choose a point as a starting point, and calculate dot product of the normal vector between the point and K nearest neighbors.

$$n_i\cdot n_j<0 \quad (i<j) \tag{2}$$

Above holds, if the angle $\arccos\,(n_i\cdot n_j/|n_i\cdot n_j|)$ between two normal vectors is greater than 90, invertn_j. Traversal all points until all normal vectors are adjusted.

2.2. Calculating the curvature

A quadratic surface was fitted to K nearest neighbors of point p to estimate the curvature of point p.

$$z=r(x,y)=a_0x^2+a_1y^2+a_2xy+a_3x+a_4y+a_5 \tag{3}$$

The least square method was used to estimate the parameters a_0, a_1,a_2, a_3, a_4, a_5 of this quadratic surface, and the Gaussian curvature K and the mean curvature H are calculated by the differential geometry:

$$K=\frac{LN-M^2}{2(EG-F^2)}. \tag{4}$$

$$H=\frac{EN-2FM+GL}{2(EG-F^2)} \tag{5}$$

where $E=r_x\cdot r_x$, $F=r_x\cdot r_y$, $G=r_y\cdot r_y$, $L=r_{xx}\cdot n$, $M=r_{xy}\cdot n$, $N=r_{yy}\cdot n$, and r_x, r_y, r_{xx}, r_{yy}, r_{xy} are the partial derivatives of the quadratic surface.

The principal curvatures k_1, k_2 are calculated by the Gaussian curvature K and the mean curvature H:

$$\begin{cases} k_1=H-\sqrt{H^2-K} \\ k_2=H+\sqrt{H^2-K} \end{cases}. \tag{6}$$