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A new methodology in fast and accurate matching of the 2D and 3D point clouds extracted by laser scanner systems

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ABSTRACT

Registration of the point clouds is a conventional challenge in computer vision related applications. As an application, matching of train wheel profiles extracted from two viewpoints is studied in this paper. The registration problem is formulated into an optimization problem. An error minimization function for registration of the two partially overlapping point clouds is presented. The error function is defined as the sum of the squared distance between the source points and their corresponding pairs which should be minimized. The corresponding pairs are obtained thorough Iterative Closest Point (ICP) variants. Here, a point-to-plane ICP variant is employed. Principal Component Analysis (PCA) is used to obtain tangent planes. Thus it is shown that minimization of the proposed objective function diminishes point-to-plane ICP variant. We utilized this algorithm to register point clouds of two partially overlapping profiles of wheel train extracted from two viewpoints in 2D. Also, a number of synthetic point clouds and a number of real point clouds in 3D are studied to evaluate the reliability and rate of convergence in our method compared with other registration methods.

1. Introduction

2D or 3D reconstruction of an object has applications in many areas such as railway visual inspection, reverse engineering, robot navigation, mold fabrication, etc. [1]. However, the most recent 3D measurement methods to model objects reconstruct only a part of the whole object. In order to achieve a complete 3D model it is necessary to register several parts of the same object. 2D or 3D data are obtained by a number of techniques such as laser scanning [2], structured light [3] or stereovision [4–6]. In order to register different views of the same object, Euclidean motion between them should be determined. In the beginning, a rough initial estimation of the motion is obtained, namely *coarse registration*. There are diverse methods to coarsely register point clouds [7–12]. Eventually, estimation of motion should be obtained from a previously known coarse registration with the better estimate, known as the *fine registration*.

In fine registration, the aim is to obtain a more accurate solution of the Euclidean motion mapping two point clouds into a single coordinate space by iteratively minimizing the distance between them [13]. The distance between the point clouds is defined as the distance between the corresponding points on both of them. By minimizing this distance, the transformation matrix for the fine registration point clouds is refined. The best-known methods for the fine registration of point clouds are the Iterative Closest Point (ICP) algorithms [13]. ICP can be divided into two steps: (1) determination of the corresponding points between two datasets and (2) estimation of the transformation matrix between the two cloud points. These steps are iterated until convergence.

ICP has many variations which can be classified into three approaches based on the finding the correspondences, namely point-to-point, point-to-projection and point-to-surface. Besl and McKay [14] proposed a point-to-point algorithm of the most common methods for the fine registration. They used closest point in a target dataset as a corresponding point for the source point in the source dataset, and the distance between them is minimized to determine the transformation matrix. This method is easy to use but has a large defect: the nearest point is not necessarily a good choice as a corresponding point and a false corresponding pair is introduced thorough this method, which limits the performance of the algorithm.

Another approach is point-to-projection method. In this pattern, the correspondence of a source point is found by projecting the source point onto the destination surface form its point of view [15,16]. Although this approach can operate rapidly, the registration accuracy is not good enough.

The point-to-surface approach is known to be the most accurate and widely used approach due to its precision and robustness [7]. The aim of this method is to find the transformation matrix, relatively by minimizing the error function of

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distances between points of corresponding pairs. The most widely used approach is the point-to-plane proposed by Chen and Medioni [17]. The algorithm finds a tangential plane at corresponding point by fitting plane. Then, the distance between the source point and the surface is minimized, instead of distance between source point and its nearest point. There are some other point-to-surface methods such as point-to-NURBS [19] and point-to-B-spline [20] approaches. In these methods finding the intersection point to the target is a time-consuming task but they converge in less iterations. The point-to-surface method has higher accuracy and efficiency in comparison with the point-to-point and point-to-projection methods because it is less likely to be influenced by local minimum [7].

As a new methodology, this article presents a framework for pair-wise registration of the point clouds. In this framework, point-to-plane ICP variant is minimized to the special case of the general optimization problem. The optimization function is defined to be the sum of the squared distance between the source points and their target planes, which should be minimized. The target planes are obtained through the Principal Component Analysis (PCA). Employing the PCA planes, instead of the least square surface fitting, makes the algorithm to run faster. We utilize this algorithm to register point clouds in 2D and 3D. The experimental results on a number of real point clouds show that the proposed algorithm can obtain accurate solution in the presence of noise.

This paper has different sections; initially, a brief overview of the proposed method is presented in Section 2. Then, Sections 3 and 4 present registration methodology in 2D and 3D cases, respectively. Section 5 explains how to employ the PCA to fit destination planes. Sections 6 and 7 present computing squared distance function in 2D and 3D cases, respectively. Section 8 discusses the Convergence Issues and eventually experimental results are presented in Section 9.

2. Problem definition and method discussion

This section provides an overview of the proposed method after a brief description to procedure of the ICP algorithm. Assume two corresponding point clouds P (on the source surface) and Q (on the target surface) in R^d and that the number of the corresponding pairs is n. Registration task here is to estimate a rigid transformation T, which is composed of the rotation matrix R and translation vector t, to minimize an objective function [13]:

$$E(R,t)=\frac{1}{n}\sum_{k=1}^{n}||Q_k-(RP_k+t)||^2 \tag{1}$$

in which symbol $||a||$ denotes the Euclidean norm of vector $\vec{a}$. In the homogeneous coordinate, T can be expressed as:

$$T=T(\alpha,\ \beta,\ \gamma,\ t_x,\ t_y,\ t_z)=\begin{bmatrix} C\alpha\,.\,C\beta & C\alpha\,.\,S\gamma-S\alpha\,.\,C\gamma & C\alpha\,.\,C\gamma+S\alpha\,.\,S\gamma & t_x \\ S\alpha\,.\,C\beta & S\alpha\,.\,S\beta\,.\,S\gamma+C\alpha\,.\,S\beta\,.\,C\gamma & S\alpha\,.\,S\beta\,.\,C\gamma+C\alpha\,.\,S\gamma & t_y \\ -S\beta & C\beta\,.\,S\gamma & C\beta\,.\,C\gamma & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

where cx and sx stand for $\cos x$ and $\sin x$, respectively. So, in general, the corresponding transformation matrix T has 6 degrees of freedom to register two point clouds. Thus, by minimizing $E(R,t)$ in Eq. (1) and by searching in transformation parameter space, such a transformation for registration can be found. The following set of equations should be consequently satisfied

$$\frac{\partial E}{\partial \alpha}=0,\ \frac{\partial E}{\partial \beta}=0,\ \frac{\partial E}{\partial \gamma}=0,\ \frac{\partial E}{\partial t_x}=0,\ \frac{\partial E}{\partial t_y}=0,\ \frac{\partial E}{\partial t_z}=0 \tag{3}$$

The problem solving process is non-linear and it is difficult to find an explicit solution. To overcome this problem some iterative method must be utilized. In addition, $E(R,t)$ may not be convex in general and there is no guarantee that a global minimum can be achieved by an iterative procedure [16]. For the two established corresponding point clouds, the least-square method can be used to find the transformation parameters. Therefore, the main problem is to establish correspondences. Here, an efficient algorithm i.e. the point-to-plane approach proposed by Chen and Medioni [17] is employed for the establishment of point matches for robust and accurate free-form 2D or 3D registration. The objective function converts to an error minimization function:

$$E(R,t)=\sum_{k=1}^{n}d^2((RP_k+t),\Pi_q) \tag{4}$$

where d can be the point-to-plane distance of Chen and Medioni and Π_q is the target plane on the destination dataset.

In the point cloud setting, the source and target datasets are not arbitrary collections of points, but are sampled from some underlying surfaces Π_p and Π_q. In this case, it is more appropriate to minimize the distance from the source point cloud to the plane represented by the target dataset.

A point-to-plane ICP variant based on the Principal Component Analysis (PCA) to obtain tangent planes is proposed to improve the accuracy and robustness of 2D and 3D point clouds registration. At the start, surface reconstruction using PCA variance approach is provided to describe the overlapping region of the two datasets. Subsequently, for a point on the source dataset, p_k its nearest point q'_k is defined as its projection onto the destination surface in the direction of its normal vector. Then, the corresponding point q_k is defined on the tangent plane, so that its distance to its source point is minimized as shown in Fig. 1. A set of correspondences is created by the use of this method. Next, we adopt an efficient constraint to reject unreliable correspondences. The constraint is a distance threshold. Finally, the transformation parameters are estimated by using the refined correspondences to iteratively minimize the error function. The process for estimating transformation parameters in 2D and 3D cases is discussed in the next sections.

3. 2D Registration

At any point $X=[x,y]\in R^2$, the availability of a 2nd degree polynomial approximant F^* is assumed such that $F^*(X)\approx d^2(X,\Pi_p)$.$F^*$ is defined as follows:

$$F^*=Ax^2+Bxy+Cy^2+Dx+Ey+F \tag{5}$$

where A, B, C, D, E and F are the approximant coefficients. In a quadratic form, F^* is represented by

$$F^*=[x,y,1]\,Q_X\,[x,y,1]^T \tag{6}$$

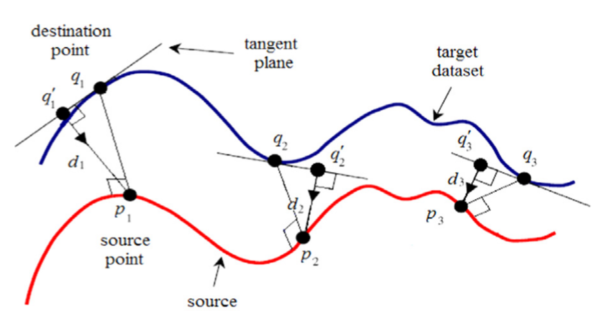

Fig. 1. Source points (p_1,p_2,p_3) and their closest point on destination cloud point (q_1,q_2,q_3) to find the correspondence point. (d_1,d_2,d_3) are point-to-plane distances.