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Matching of 3D surfaces and their intensities ☆

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Abstract

3D surface matching would be an ill conditioned problem when the curvature of the object surface is either homogenous or isotropic, e.g. for plane or spherical types of objects. A reliable solution can only be achieved if supplementary information or functional constraints are introduced. In a previous paper, an algorithm for the least squares matching of overlapping 3D surfaces, which were digitized/sampled point by point using a laser scanner device, by the photogrammetric method or other techniques, was proposed [Gruen, A., and Akca, D., 2005. Least squares 3D surface and curve matching. ISPRS Journal of Photogrammetry and Remote Sensing 59 (3), 151–174.]. That method estimates the transformation parameters between two or more fully 3D surfaces, minimizing the Euclidean distances instead of *z*-differences between the surfaces by least squares. In this paper, an extension to the basic algorithm is given, which can simultaneously match surface geometry and its attribute information, e.g. intensity, colour, temperature, etc. under a combined estimation model. Three experimental results based on terrestrial laser scanner point clouds are presented. The experiments show that the basic algorithm can solve the surface matching problem provided that the object surface has at least the minimal information. If not, the laser scanner derived intensities are used as supplementary information to find a reliable solution. The method derives its mathematical strength from the least squares image matching concept and offers a high level of flexibility for many kinds of 3D surface correspondence problem.

Keywords: surface matching; least squares matching; point clouds; registration; laser scanning; intensity matching; attribute information

1. Introduction

For 3D object modelling, data acquisition must be performed from different standpoints. The derived local point clouds must be transformed into a common system. This procedure is usually referred to as registration. In the literature, several attempts have been described concerning the registration of 3D point clouds. One of the most popular methods is the Iterative Closest Point (ICP) algorithm developed by Besl and McKay (1992), Chen and Medioni (1992) and Zhang (1994). The ICP is based on the search for pairs of nearest points in the two sets and estimates the rigid body transformation that aligns them. Then, the rigid body transformation is applied to the points of one set and the procedure is iterated until convergence is achieved.

In Besl and McKay (1992) and Zhang (1994) the ICP requires every point in one surface to have a corresponding point on the other surface. Alternatively, the distance between the transformed points in one

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surface and corresponding tangent planes on the other surfaces was used as a registration evaluation function (Chen and Medioni, 1992; Bergevin et al., 1996; Pulli, 1999). The point-to-tangent plane approach gives a better registration accuracy than the point-to-point approach.

The parameters of the rigid body transformation are generally estimated by the use of closed-form solutions, mainly singular value decomposition and quaternion methods. Eggert et al. (1997) and Williams et al. (1999) provide an extensive review and comparison. The closed-form solutions cannot fully consider the statistical point error models. Zhang (1994) and Dorai et al. (1997) weighted the individual points based on a priori noise information. Williams et al. (1999), Guehring (2001) and Okatani and Deguchi (2002) proposed methods that can model the anisotropic point errors.

The gradient descent type of algorithms can support full stochastic models for measurement errors, and assure a substantially lower number of iterations than the ICP variants (Szeliski and Lavallee, 1996; Neugebauer, 1997; Fitzgibbon, 2001). The Levenberg–Marquardt method is usually adopted for the estimation.

The ICP, and in general all surface registration methods, requires heavy computations. Strategies employed to reduce the computation time are: reduction of the number of iterations, reduction of the number of employed points, and speeding up the correspondence computation. Extensive surveys on commonly used methods are given in Jost and Huegli (2003), Park and Subbarao (2003) and Akca and Gruen (2005).

Several reviews and comparison studies on surface registration methods are available in the literature (Jokinen and Haggren, 1998; Williams et al., 1999; Campbell and Flynn, 2001; Rusinkiewicz and Levoy, 2001; Gruen and Akca, 2005).

When the surface curvature is either homogeneous or isotropic, as is the case with all first or second order surfaces, e.g. plane or spherical surfaces, the geometry-based registration techniques will fail. In some studies, surface geometry and intensity (or colour) information have been combined in order to solve this problem. Maas (2001) used the airborne laser scanner reflectance images as complimentary to the height data for the determination of horizontal shift parameters between the laser scanner strips of flat areas. Roth (1999) and Vanden Wyngaerd and Van Gool (2003) used feature-based methods in which interest points and regions are extracted from the intensity images. More often the intensity information is processed as an extra distance value under an ICP algorithm in order to reduce the search effort for corresponding point pairs or in order to eliminate the ambiguities due to inadequate geometric information on the object surface (Weik, 1997; Johnson and Kang, 1999; Godin et al., 2001; Yoshida and Saito, 2002).

In a previous work, an algorithm for the least squares matching of overlapping 3D surfaces, called Least Squares 3D Surface Matching (LS3D), was proposed (Gruen and Akca, 2005). It estimates the transformation parameters between two or more fully 3D surfaces, using the Generalized Gauss–Markoff model, minimizing the sum of the squares of the Euclidean distances between the surfaces. This formulation gives the opportunity of matching arbitrarily oriented 3D surfaces simultaneously, without using explicit tie points. The mathematical model introduced in this paper is a generalization of the least squares image matching method, in particular the method given by Gruen (1985). For the details of the mathematical modelling and execution aspects, the reader is referred to Gruen and Akca (2005).

When the object surface lacks sufficient geometric information, i.e. homogeneity or isotropicity of curvatures, the basic algorithm will either fail or find a side minimum. This work proposes a solution in which available attribute information, e.g. intensity, colour, temperature, etc., is used to form quasisurfaces in addition to the actual ones. The matching is performed by simultaneous use of surface geometry and attribute information under a combined estimation model. The formation of the quasisurfaces and mathematical modelling of the problem are given in the following section. The experimental results based on terrestrial laser scanner point clouds are presented in the third section.

2. Simultaneous matching of surface geometry and intensity

2.1. Problem definition

$f(x, y, z)$, being the template surface, is a discrete 3D function, which represents an object surface. $g(x, y, z)$, being the search surface, is its conjugate part, which was digitized from a different viewpoint or at a different time or by a different sensor. Every sampled element of the template and the search surfaces has an attribute value in addition to the 3D coordinates.

Matching is established in an ideal case:

$$f(x, y, z) = g(x, y, z) \tag{1}$$

Because of the effects of random error, Eq. (1) is not consistent. Therefore, a true error vector $e(x, y, z)$ is