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Point cloud comparison under uncertainty. Application to beam bridge measurement with terrestrial laser scanning



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ABSTRACT

In this paper a methodology to compare two point clouds of an object, obtained with different equipment or in different conditions, is proposed. First, the point clouds are registered to the same reference system using an iterative algorithm that performs a rigid body transformation. Then, the standard deviation of the measurements is estimated, in order to evaluate the uncertainty in the measurements. Afterwards, two surfaces are adjusted to each of the point clouds by means of a kernel smoothing technique and compared. Finally, the effect of uncertainty in the point coordinates is considered by means of a bootstrap analysis.

The methodology was used to compare two point clouds of a beam bridge measured using two different types of terrestrial laser scanner (time-of-flight and phase-shift based systems). According to the results obtained, some statistically significant differences exist between both point clouds.

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1. Introduction

There are many practical situations where technicians have to make decisions about the most appropriate equipment for a particular task. For instance, they have to choose between different terrestrial laser scanners (TLS) available on the market. Each of these devices has its own technical characteristics, accuracy and precision of the point coordinates being two of the most important for the technicians. Usually the cost of the measuring equipment increases with accuracy and precision.

Both characteristics, accuracy and precision, are given by the manufacturer for an isolated point. However, terrestrial laser scanners are not designed to measure isolated points but to construct surface models of the measured objects [1]. In fact, these devices are able to measure

http://dx.doi.org/10.1016/j.measurement.2014.02.013 0263-2241/© 2014 Elsevier Ltd. All rights reserved. millions of points in few minutes. By adjusting surfaces to point clouds, factors such as the point density becomes relevant for the accuracy of the models [2–4].

Accuracy and precision of TLS measurements influence the quality of the surface model adjusted to a point cloud representing a real object. Consequently, point cloud comparison can be used to detect differences between TLS systems. Point cloud comparison is also one of the tools implemented in many point cloud processing software [5,6] given its practical use in inspection work [7]. Change detection is another common application of point cloud comparison [8,9].

Although point cloud comparison can be performed directly [10], many approaches for point cloud comparison start adjusting surfaces to at least one of the two point clouds and transforming the initial irregular meshes to a common regular mesh [11]. Surface matching is then accomplished. The ICP (iterative closest point) algorithm is one of the basic algorithms for surface matching [12]. Once the two point clouds are registered in the same



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coordinate system, the differences between the two point clouds are determined by calculating the vectors between corresponding nodes of the two meshes.

Usually, software for point cloud comparison provides graphics of displacement vectors and statistics concerning the relative position of two point clouds. This information is useful to estimate the magnitude and location of the distance vectors between the point clouds. However, the comparison is normally done assuming that there is no uncertainty in their position. Instead, in this paper we consider a point cloud just as a realization of a stochastic process. Accordingly, we have developed a methodology to compare point clouds that provides, besides the point to point distances, an estimation of the uncertainty on these distances and information regarding the statistical significance of the differences between the point clouds.

2. Methodology

2.1. Point cloud registration

Many types of sensors such as rotating laser scanners and stereo and 3D cameras with all their variants, produce 3D point clouds from different stations and with different angular orientations which need to be registered (spatially aligned) in a common coordinate system. This registration process is formulated mathematically through a rigid body transformation whose six parameters (one translation and three angles in 3D space) are calculated by the iterative closest point (ICP) algorithm.

The ICP algorithm is one of the methods commonly used for 3D shape alignment. It is used for real-world model construction, robot navigation, inspection and reverse engineering among other applications. Since its introduction [13,12] the ICP algorithm has derived in many different variants [14]. However, the main concept remains stable and can be stated as the iterative search of the rigid body transformation between two different point clouds which minimizes an error metric through repeated generation of pairs of corresponding points on the clouds.

The process starts with an initial estimation of the six degrees of freedom for the rigid body transformation and the selection of points in both clouds. A matching between corresponding pairs is established after applying the actual 3D transformation to the original point cloud and weighted appropriately. Some of the pairs are then rejected under different criteria and an error metric value is calculated for the remaining pairs in a process which tries to minimize the total error.

Some formulations of the ICP algorithm use the point to point error metric [12], others use the point to plane metric which tries to minimize the sum of the squared distances between each source point and the tangent plane at its corresponding point in the destination point cloud [15]:

$$M = T(t_x, t_y, t_z) R(\alpha, \beta, \gamma)$$
(1)

$$M_{opt} = argmin \sum_{i} ((Ms_i - d_i))^2$$

where *M* represents a rigid body transformation matrix (translation *T* and rotation *R*), s_i is a source point vector,

 d_i is a destination point vector and n_i is the tangent plane normal in the destination point. If the initial estimation is reasonable, the overlap between the point clouds is sufficient and the process reaches to a local minimum with the best transformation between point clouds.

2.2. Surface estimation

Once the point clouds have been registered in the same coordinate system, a surface is adjusted to each of them by means of a nonparametric estimation method. Let us consider (X, Y, Z) the spatial co-ordinates of each point on the object surface and assume that the third co-ordinate Z can be obtained from (X, Y) using an unknown function m(X, Y), which represents a kind of *smooth* surface, so that Z = m(X, Y). Given that m is not known, we need to estimate this function using the point cloud $(X_i^{\bullet}, Y_i^{\bullet}, Z_i^{\bullet})$ for i = 1, ..., n. Each of these points can be understood as a measure of the real point (X_i, Y_i, Z_i) on the object surface, so that

$$(X_i^{\bullet}, Y_i^{\bullet}, Z_i^{\bullet}) = (X_i, Y_i, Z_i) + (\varepsilon_i^X, \varepsilon_i^Y, \varepsilon_i^Z)$$

$$\tag{2}$$

where $(\varepsilon_i^x, \varepsilon_i^y, \varepsilon_i^z)$ represents the measurement error on the *i*th point.

For any given point (x_0, y_0) , a smoothed version of the principal surfaces [16] is proposed to obtain an estimation of $m(x_0, y_0)$. These estimators are based on the fact that surface (x, y, m(x, y)) can be approximated by a plane:

$$m(x,y) \approx a + bx + cy + d = 0$$

in values (x, y) near (x_0, y_0) . Thus, the normal vector of the plane (a, b, c) can be obtained as the smallest component of a local principal component analysis. The proposed procedure is as follows:

• For each point *i* = 1,...,*n* a weighting function is computed:

$$W_{i} = W_{h} (X_{i}^{\bullet} - x_{0}, Y_{i}^{\bullet} - y_{0})$$

= $\exp \left\{ -\frac{(X_{i}^{\bullet} - x_{0})^{2} + (Y_{i}^{\bullet} - y_{0})^{2}}{h} \right\}$ (3)

Note that, the weight W_i depends on the Euclidian distance between (x_0, y_0) and $(X_i^{\bullet}, Y_i^{\bullet})$ and, in addition, contains a smoothing parameter h. In order to simplify the notation, it will be assumed that weights W_i have been recentered so $\sum_{i=1}^{n} W_i = 1$.

• Compute the weighted sample covariance matrix

$$\hat{\Sigma} = \begin{pmatrix} \hat{\sigma}_X^2 & \hat{\sigma}_{XY} & \hat{\sigma}_{XZ} \\ \hat{\sigma}_{XY} & \hat{\sigma}_Y^2 & \hat{\sigma}_{YZ} \\ \hat{\sigma}_{XZ} & \hat{\sigma}_{YZ} & \hat{\sigma}_Z^2 \end{pmatrix}$$
(4)

with

$$\hat{\sigma}_X^2 = \sum_{i=1}^n W_i (X_i^{\bullet})^2 - \bar{X}^{\bullet 2}, \quad \hat{\sigma}_Y^2$$
$$= \sum_{i=1}^n W_i (Y_i^{\bullet})^2 - \bar{Y}^{\bullet 2}, \quad \hat{\sigma}_Z^2 = \sum_{i=1}^n W_i (Z_i^{\bullet})^2 - \bar{Z}^{\bullet 2}$$

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