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Evaluation of point cloud registration using Monte Carlo method

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ABSTRACT

Supervision and control are one of the most important steps while executing a construction project and their automation remains an area of growing interest. LiDAR systems provide accurate point clouds with geometric information that can help to improve the automation of survey control. Alignment of the point clouds acquired from a number of scan positions is a fundamental issue regarding surveying accuracy and is frequently carried out in two steps: coarse and fine registration. Fine registration can be achieved automatically by means of an Iterative Closest Point (ICP) procedure. This work presents a Monte Carlo based method to quantify the reliability of a coarse registration step that would enable the automation of the alignment. The method consists of verifying the tolerance of a particular ICP implementation to coarse registration errors. Results show that the ICP alignment used works fine when coarse registration errors are lower than $18°$ for rotations and 1 m for translations. These values were similar for four case studies analysed. Quantifying these limits is crucial for operations such as robotic stop & go surveying, where coarse alignment is based on Simultaneous Location and Mapping (SLAM) and fine alignment is achieved through ICP.

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1. Introduction

Over the last decades, safety and quality management processes have gained importance in construction industry. A systematic dimensional and quality assessment of as-built construction components with planned works is essential for the timely and successful completion of a construction process, and thereby saving costs.

Progress tracking analysis of construction elements is traditionally based on visual inspections and reports performed by experienced inspectors. Dimensional analysis is mostly based on the use of remote sensing instruments such as Total Stations. Despite of their high accuracy, their results are dependent on trained operators and time-consuming procedures $[1-3]$. On the other hand, Terrestrial Laser Scanners (TLS) have been receiving an increasing attention for collecting and analysing three-dimensional as-built data. Point clouds acquired with TLS have a relatively higher quality, the acquisition process is faster, and therefore practical at large scale $[4-6]$. A major drawback of TLS indoor systems is given by the impossibility of using global navigation satellite systems (GNSS) for georeferencing and automatically registering the scanned data. Indoor systems tend to use navigation techniques based on high performance and cost inertial systems such as laser rings [\[7\],](#page--1-0) or Simultaneous Localization and Mapping (SLAM) techniques [\[8\].](#page--1-0)

Although there are mapping systems that provide 3D point clouds based on 3D positioning and 2D laser scanning [\[9\],](#page--1-0) in most of the survey processes, data is acquired from nearby locations in a static way, similar to traditional Total Station surveying [\[10\].](#page--1-0) For the first kind of systems, point cloud accuracy is mainly based on the accuracy of the navigation system. On the other hand, in traditional TLS-surveying, accuracy is determined by the registration of successive scan positions. In this way, the sensor is placed in different positions and data must be combined and registered into the same coordinate system. If the LiDAR location is achieved using an autonomous robot, the methodology is called stop & go scanning [\[11\]](#page--1-0), where the robot position and orientation (POSE) can be obtained by means of SLAM techniques $[8]$ and subsequently applied to point cloud coarse registration. Although the use of SLAM for registration reduces human intervention, the drifts in robot positioning can worsen coarse registration accuracy, which is essential for a subsequent fine registration process. Fine registration can be carried out by point matching-methods such as the Iterative Closest Point (ICP) [\[12\].](#page--1-0)

In order to obtain a single model, the different point clouds obtained after the acquisition step must be aligned into a single coordinate system. This alignment is frequently performed in two steps. The first one consists of a coarse alignment of the point clouds that facilitates the second step, where the fine alignment is

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typically performed using ICP. There are different ICP flavours that can be used for robust registration. Recent improvements to the registration process come from coarse alignment and are focused on adapting image processing techniques to 3D point clouds, in order to obtain a number of representative and distinctive points or characteristics that could be used for registration purposes. Theiler et al. [\[13,14\]](#page--1-0) present the use of geometric Harris and SIFT keypoints in the 3D point clouds applied to alignment. SIFT keypoint properties based on differences of Gaussians (DoG) are used to perform a coarse alignment adopting a modification of the 4- Points Congruent Sets algorithm (4PCS). The paper shows good results for the different point clouds, especially after performing the fine alignment with ICP. The main drawback is the loss of quality when the registration is performed on a symmetric environ-ment. Mellado et al. [\[15\]](#page--1-0) present another modification of the 4PCS, with a focus on time performance. The main improvement is achieved by limiting the amount of points used in the search step to a number of spheres with different radius. Rusu et al. [\[16\]](#page--1-0) present a point descriptor based on a histogram containing geometric information of the neighbourhood of each point. All these presented features are a valuable kernel for coarse alignment. Wein-mann and Jutzi [\[17\]](#page--1-0) propose a method that incorporates the usage of both range and intensity properties of scanned points. Features are obtained from the application of SIFT to a 2D projection of the intensity values. After a matching step and reliability assessment, the most distinctive values are used as keypoints for the registration.

The main contribution of the present work is the presentation of a Monte Carlo evaluation method that evaluates the reliability of the automatic registration process. In this particular case the evaluation method is implemented to determine whether or not autonomous SLAM positioning accuracy is acceptable for ICP fine registration, defining the feasibility of autonomous systems for accurate indoors surveying.

For this work, eight point clouds corresponding to four case studies were collected maximizing building coverage and avoiding shadowed and occluded areas. Point clouds gathered from these so called scan-positions are combined in a unique coordinate system through a registration process that consists of two successive procedures: a point-based coarse registration and an ICP-based fine registration. Coarse registration is carried out by manually selecting the corresponding points and ICP algorithm is automatically applied to the whole point clouds, minimizing the differences between both of them. Accurate point clouds can be provided with this methodology.

The convergence of a particular ICP registration algorithm is weighed depending on the lack of accuracy of previous coarse registration. Such lack of accuracy is modelled as a rigid body transformation applied to one of the point clouds. The manuscript is structured as follows: Section 2 shows the materials and methods, Section [3](#page--1-0) the results and discussion, and Section [4](#page--1-0) the conclusions.

2. Materials and methods

2.1. 3D LiDAR

Data acquisition is taken with a phase-shift LiDAR. The Faro Focus3D X 330 has a range of 0.6–330 m, with an error of \pm 2 mm. It can measure at a maximum speed of 976,000 points per second and provides images up to 70 mega-pixels. It also includes several sensors such as a Global Navigation Satellite System (GNSS), a compass, a barometric sensor for altitude measurement, and a dual axis compensator.

2.2. Point clouds dataset

The methodology presented in this study is tested in four case studies: a classroom laboratory, a hall and a corridor, all in the School of Mining Engineering at University of Vigo, and a garage at a residential building. The four zones are scanned from two scan-positions [\(Fig. 1\)](#page--1-0), obtaining a data set that consist of eight point clouds of around 5–27 million points. In order to reduce computation time during Monte Carlo evaluation and further processing, the point clouds are subsampled with an octree filter ([Table 1\)](#page--1-0). Octree filter not only allows to reduce size of the original point clouds, but also helps to keep a well distributed point cloud, evening out the original varying point distribution [\[18,19,13\].](#page--1-0)

As the accuracy and the performance of the coarse registration methods is of no interest in this work, the scan positions of the first three datasets were chosen really close to each other. The main intention was to avoid occlusions and obtain similar results in the experiments. The last dataset was taken as more realistic situation. [Table 2](#page--1-0) shows the displacements between each coordinate axis and the absolute distance from the scan positions.

2.3. Monte Carlo testing methodology

2.3.1. Monte Carlo method

The main idea in the implementation of the Monte Carlo method in this work is to assess the tolerance allowed by the ICP algorithm. Thus, the Monte Carlo method would be used to obtain variations in the input point clouds for the fine registration process. Steps used in the Monte Carlo based method are summarised in [Fig. 2](#page--1-0). Coarse registration, which usually represent the first step in the alignment procedure, is not under analysis in this work. However, the Monte Carlo simulation requires the result from this operation as the input data. As a consequence, a ground truth (GT) value used for comparison is needed. Point clouds corresponding to each of the test spaces are accurately coarse registered. As discussed above, this preliminary registration consists of a manual coarse registration with mean error lower than 7 mm in all cases ([Table 3\)](#page--1-0). Coarse registration process is done using Cloud Compare software belonging to the first part of the whole procedure.

Once the coarse aligned point clouds are computed, the Monte Carlo method can start. The method works with simulation of N repetitions of one or more random variables. The most common random variables used are the ones which present a Gaussian distribution. The Gaussian distribution is characterised by a mean value and the standard deviation (or variance). For this simulations the random variables have been decided to be the translation and the rotation among the three geometrics coordinates T_x, T_y, T_z and \mathbf{R}_{x} , \mathbf{R}_{y} , \mathbf{R}_{z} . The method relies on the generation of the N repetitions of the random variables defined by Eq. (1). The mean of the Gaussian distribution is decided to be set to zero so the changes over the geometric coordinates are centred on the coarse registration result.

$$
\mathbf{T_x} \sim \mathcal{N}(\mu = 0, \sigma_t^2)
$$

\n
$$
\mathbf{T_y} \sim \mathcal{N}(\mu = 0, \sigma_t^2)
$$

\n
$$
\mathbf{T_z} \sim \mathcal{N}(\mu = 0, \sigma_t^2)
$$

\n
$$
\mathbf{R_x} \sim \mathcal{N}(\mu = 0, \sigma_r^2)
$$

\n
$$
\mathbf{R_y} \sim \mathcal{N}(\mu = 0, \sigma_r^2)
$$

\n
$$
\mathbf{R_z} \sim \mathcal{N}(\mu = 0, \sigma_r^2)
$$

\n(1)

where μ represents the mean value, σ_t^2 the variance in translation, σ_r^2 the variance in rotation, and $\mathcal{N}(\mu, \sigma^2)$ is a normal distribution with mean μ and variance σ^2 .

The number of events (or repetitions) represent an important issue in this type of simulations. Hence, a convergence test Download English Version:

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