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An evaluation of intensity augmented ICP for terrestrial LiDAR data registration

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Abstract: While using laser scanner for map-making or developing 3D models of objects, it is important to scan a site or an object from multiple viewpoints. These different scans are integrated to generate a complete point cloud which is then used for developing the map or 3D model of the site. ICP (Iterative Closest Point) is a standard algorithm for registration of point clouds. However, in the absence of marked features which are geometrically distinct in the point clouds, which are being combined, this method sometime fails. This paper exploits the radiometric data that are always obtained along with the coordinates and devises a novel approach for scan registration. Before using radiometric data in registration process, the data are normalized. The algorithm presented in this paper works in two stages- Intensity Augmented ICP (IAICP) for coarse registration stage and conventional geometric ICP at the fine registration stage. The proposed approach is successfully applied to a few test data captured by Optech ILRIS 36-D resulting in an accurate estimation of the transformation parameters. A comparison of the conventional and intensity augmented registration approaches is also presented. The results indicate the supremacy of IAICP over the ICP, as the latter is found to fail in geometrically confusing cases while the intensity augmented ICP gives satisfactory result in such cases.

Keywords: ICP, Intensity Augmented ICP, Radiometric data, Scan registration, Multiple scans

1. Introduction

The process of 3D modelling of objects and terrain has changed in a significant manner since the availability of laser scanners. As laser scanners are capable of capturing billions of data points in a single hour, in comparison to about 60-80 data points in the case of Total Station, the speed of data capture has increased multifold. In addition, the data captured are very comprehensive and make it possible to map or model fine details, which would otherwise go unnoticed in the case of Total Station survey. There are several advantages of using laser scanner for mapping or 3D modeling and in view of the same laser scanners are replacing Total Station based mapping to some extent in some applications.

A large number of LiDAR based applications are envisaged in the near future. This has set the current focus on generating more accurate and true representations of the collected data. This will not be possible unless a complete 3D representation on the target can be generated by registration of point clouds collected from different locations for the same scene. The multiple scans have their own local coordinate systems. To view the complete area of interest together all such scans are combined in a single point cloud represented in the same co-ordinate system. This single point cloud is then used for mapping or modeling the objects. The LiDAR point clouds are usually registered by placing artificial markers into the scene and manually aligning them using commercial software. Such manual alignment will be cumbersome for large number of scans and will increase human intervention in the field. Most available commercial software for 3D LiDAR data processing perform registration manually. Automatic methods in such software usually give undesirable results and consume considerable amount of processing time. This paper proposes a novel algorithm which performs automatic registration of 3D point clouds eliminating the process of introducing artificial markers into the scene thereby making the registration process simpler.

2. Related work

The conventional methods of integrating multiple scans employ a few control points in the overlap area of the master and slave scans. With the rigid body transform, developed using these control points, the slave scan is brought to the coordinate system of the master scan. This method is, however, affected by the observational errors in selecting the control points and also needs manual intervention as the control points are selected manually. In order to avoid these limitations a common method for scan point cloud registration is ICP (Iterative Closest Point) algorithm (Besl and McKay, 1992). The original method was based on establishing point to point correspondences by Euclidean distance evaluation. The ICP variant proposed by Chen and Medoni (1992) analyzes the local surface approximations of the datasets. A method to incorporate the k-d tree data structure into point matching algorithm, to minimize computational time, is described in (Masuda et al., 1996). The classical ICP is susceptible to non-overlapping regions since it does not consider the overall geometry but local geometries and may lead to incorrect results by converging to local minima (Hebel and Stilla, 2007). Some approaches use only geometric data collected from the LiDAR instrument whereas others incorporated radiometric data along with spatial coordinates. Godin et al. (1994) used both range information and intensity images in the version of ICP Algorithm for point cloud registration. In his approach, the intensity is first be converted into a viewpoint-independent feature by inverting an illumination model, by differential feature measurements or by simple clustering. Johnson and Kang (1997) used traditional ICP algorithm and modified it to use the color information provided by the scanner for creating virtual 3D environment. Hebel and Stilla (2007) propose a method for automatic registration of Laser Point Clouds from an airborne LiDAR for urban areas by incorporating the intensity of the reflected laser pulse and normal vectors of the fitted plane to attain faster convergence and higher robustness. The two -staged registration process presented by Weinmann et al. (2011) utilizes geometric and radiometric information, in the form of intensity images, derived from the TLS data for estimating the transformation parameters between two unregistered point clouds. The authors used the robust RANSAC and EPnP algorithms for coarse registration along with a single step of outlier removal and higher accuracy is attained by introducing additional geometric constraints. Altuntas (2011) discusses an experimental study on registration of 3D range images using range and intensity data where the intensity image was created from laser scanner data and the registration parameters were computed with key points extracted by Scale Invariant Feature Transform (SIFT) method from these images.

As ICP algorithm basically uses the geometric property of the scanned objects it tends to fail in situations where the objects do not possess marked geometric features, or where the geometric match still is possible even if the object is rotated e.g., a wall, a door etc. Most of the variants of ICP that were developed tend to focus on increasing the speed but not to solve this problem. Most existing algorithms for LiDAR data registration are either application specific or involve complex image processing techniques. Some demands additional data acquired from calibrated cameras. Many others produce intermediate results and make it difficult to incorporate them with standard software packages.

In view of the above the goal of this paper is to investigate the use of intensity information along with the geometric information of point clouds for their registration. This approach is based on the fact that despite the objects (overlap area between two scans) being devoid of any or sufficient number of distinctive geometric features there always is a possibility that there exist distinctive radiometric features which can be used for matching scans. The paper will show development of this new approach, called, intensity augmented ICP (IAICP), and presents some results to show its efficacy. The proposed algorithm is validated using the point clouds collected using Optech ILRIS 36-D terrestrial laser scanner. As the TLS currently available in the market widely varies in data capturing techniques, this paper only targets data sets collected using Optech ILRIS 36-D.

A preliminary version of the methodology proposed with only a few results was presented at INCA conference by Lohani and Sasidharan (2013). This paper is extension of this work with fully developed methodology and a large number of results to validate the methodology.

3. Methodology

Proposal

The proposed methodology has three basic steps. (1) Normalization of LiDAR intensity data (2) Coarse registration of LiDAR point clouds using intensity augmented ICP method (3) Fine registration using geometric ICP method. The flow chart of the proposed algorithm is given in Fig. 1.

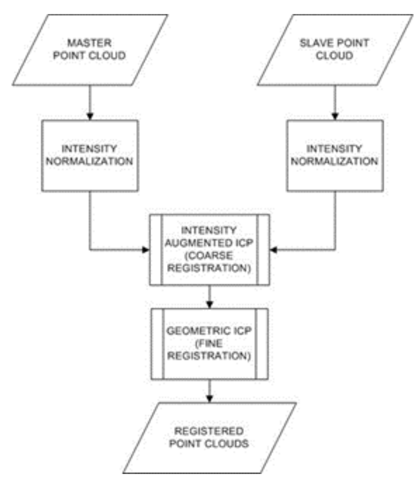

Figure 1: Flow chart of the proposed algorithm

Resources employed

ILRIS 36-D terrestrial laser scanner from Optech Inc. Canada was used in this study for collecting laser scans of the test objects. This scanner collects data in a 40 by 40 degree window, while this window can be rotated with the help of a Pan-Tilt device to cover entire 360 degree in horizontal and 180 degree in vertical. The initial data generated by ILRIS 36D were processed using the accompanying parser software to yield coordinates (x, y, z) and the intensity value for each point captured. The intensity directly provided by the instrument is called raw intensity. The 8 bit intensity data are derived from the raw intensity after applying some corrections and scaling these values to 8 bit format to improve the visual quality of the point cloud and is not available to the end user. In this paper terminology 'raw intensity' refers to the 16 bit intensity data provided by the TLS.

All algorithms developed and employed in this paper were realized through a code written in MATLAB. The mathematical background and code is beyond the scope of this paper and are not being presented.

Normalization of LiDAR intensity

Any existing method (Fang et al., 2015; Höfle, 2014; Teo and Yu, 2015) may be used for normalizing the intensity value. The method discussed in this paper is simple and specific to ILRIS 36-D. A detailed evaluation of the intensity normalization method used in this paper with different data samples is discussed in (Sasidharan, 2016). The basic steps are shown in Fig. 2.

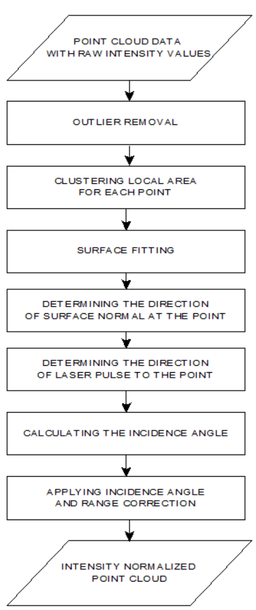

Figure 2. Flow chart for Intensity Normalization Algorithm.

Outlier elimination step removes the isolated data points, i.e., those with less than 10 nearest neighbors. A simple k-nearest neighbor ball search is employed for clustering the data. For each data point in the scan, the neighboring data points lying at a chosen radius are selected. The radial distance for the nearest neighbor ball search depends on the scan density. To apply the incident angle correction at each data point, the direction of the incident ray vector and the surface normal at each data point need to be calculated. For individual clusters formed at each data point using k-nearest neighbors, a second order polynomial surface is fit and the direction of the surface normal at that data point is determined. The incident angle is calculated by taking the inverse cosine of the ratio of the dot products of the direction of surface normal and the direction of the laser pulse at a particular point, where the latter is known in terms of the coordinates of the point where the surface normal is being computed. The incident angle calculated is true in the specific case of ILRIS 36-D because of limited angular range for single acquisition. For other instruments, this may differ and a constant angle could be added. The normalized intensity for ILRIS 36-D is then computed using the formula:

$$\boldsymbol{I_{norm}} = \boldsymbol{I_{raw}}\left(\frac{\boldsymbol{R_{act}}}{\boldsymbol{R_{ref}}}\right)^{\boldsymbol{2}}\left(\frac{\boldsymbol{1}}{\boldsymbol{\cos(i)}}\right) \quad \ldots\ldots\ldots(1)$$

where, I_{raw} and I_{norm} are raw and normalized intensities, R_{act} and R_{ref} are actual and reference ranges and i is the incident angle.

Coarse registration by intensity augmented ICP

The description of ICP algorithm is beyond the scope of this paper and can be seen in the cited references. A pseudo code for registration ins given in Annexure 1. The intensity augmented ICP implemented in this paper differs from the classical ICP, as in addition to the coordinates, the intensity information is also included in the correspondence matching search space. Before including the intensity information, the intensity normalization process, as explained above, is performed. This enables determination of the correspondences in a more abstract manner by using (x, y, z, Intensity) rather than using only pure geometric information i.e. (x, y, z). Hence the algorithm searches both intensity and spatial spaces at the same time for correspondences. For a point cloud from a terrestrial laser scanner the spatial coordinates and the intensity values cannot be directly utilized without scaling. For scaling intensity data, the z-score statistical standardization technique is used. The basic algorithm flow chart is shown in Fig. 3.

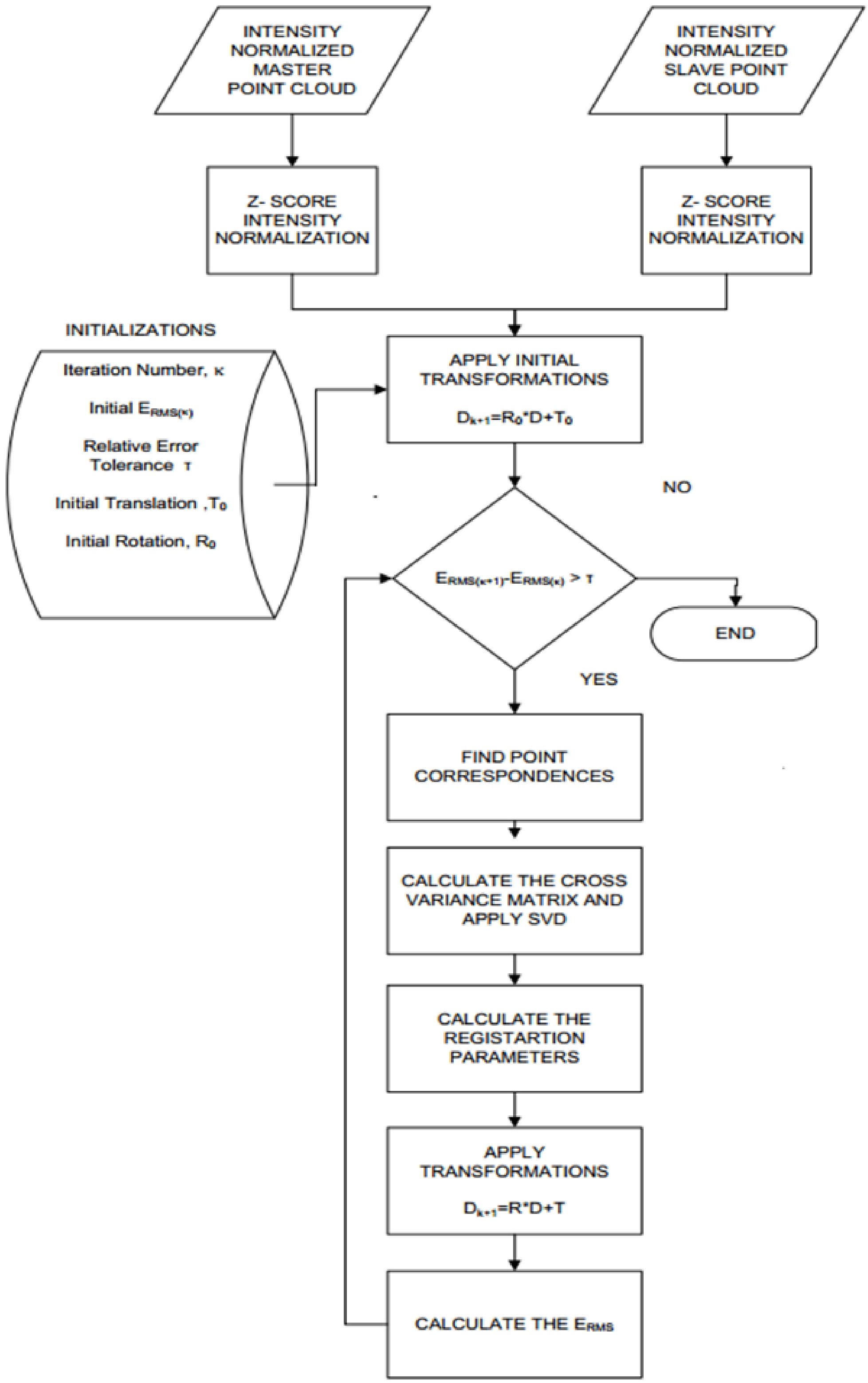

Figure 3: Course registration process-Phase I

Fine registration using geometric ICP

A pseudo code for ICP algorithm ins given in Annexure 2. The IAICP is followed by the geometric ICP in order to guarantee proper registration. In this paper, the more accurate point to plane minimization technique is used. The point to plane variant of ICP improves performance by taking advantage of the surface normal information. The point to plane algorithm minimizes the error along the surface normal (Chen and Medoni, 1992).

This minimization scheme involves two processes, viz. calculating the surface normals for the Master point cloud and then minimizing the angle between the normals of Slave and the Master point cloud. The approximate surface normals can also be computed using Principal component analysis. For computing the surface normals, four nearest neighbors are selected for each point, the Eigen vector corresponding to the smallest Eigen value represents the surface normal at that point. The flowchart for fine registration is shown in Fig. 4. The output of the ICP iteration is the 3D transformation parameter set for registration. The plane minimization technique is computationally complex and time consuming, but as the coarse registration has already been achieved, the convergence is faster.

Results and discussion

The results are aimed at proving the hypotheses that (i) intensity normalization method proposed is effective and (ii) intensity augmented ICP is an effective solution where classical ICP fails due to geometric confusion.

Intensity normalization results

The point clouds of the same materials captured from different scan locations are used for this analysis. Six sets of data were subjected to normalization technique explained above. The raw 16 bit intensity values obtained after parsing the scan data were used for normalization.

The intensity normalization results are shown in Table I. The normalization is performed for a reference range of 100 m while the average object range varied from 35 m to 50 m. The histograms that plots Intensity values vs. number of points of the raw and normalized data are shown in Fig. 5 to Fig. 7 for a few example cases. High variance in the raw intensity values is the reason for the appearance of the raw data histogram as disjointed lines.

Table 1: Intensity normalization result

Material	Scan No	Raw Mean	Raw SD	Normalizes Mean	Normalizes SD
Brick	Scan1	3290	622	44	8
Wall-I	Scan2	4365	788	53	9
Brick	Scan1	4365	788	53	9
Wall-II	Scan2	1728	361	67	14
Concrate	Scan1	418	192	104	48
Wall-I	Scan2	1385	505	147	53

Normalization result

Raw intensity values, after incidence angle and range correction, become comparable as shown by their mean and standard deviation (Table 1). From the histograms it can also be inferred that after intensity normalization, the intensities for the same material appear to have similar mean and standard deviation values and thus it can be effectively incorporated as one of the parameters for finding point to point correspondence in the ICP algorithm. In order to understand the efficacy of the normalization process quantitatively, a statistical distance between the raw and normalized intensity distributions is calculated using the ratio of the difference of the means and the sums of the standard deviations. These ratios are shown in Table II. In the case of concrete wall–I data set, this distance is 1.39 for raw data while 0.43 for normalized data, thus showing that the scans come nearer to each other after normalization.

Six sites with different geometry were chosen for studying this but for the want of space the results from only three sites are shown here. Concrete and brick structures were considered as the same were used for intensity normalization study. The registration was performed in 30 iterations and the RMS error value was computed. The RMSE value is the root of the mean of the square of the differences in the coordinates of master point and slave point after applying rotation and translation as suggested by the registration process. This is computed at each iteration of the registration. Fig. 8 to Fig. 10 show the result of Geometric ICP and Intensity Augmented ICP, while Fig. 11 to Fig. 13 show the convergence graph. The RMSE for Geometric ICP and IAICP are shown in Table 3.

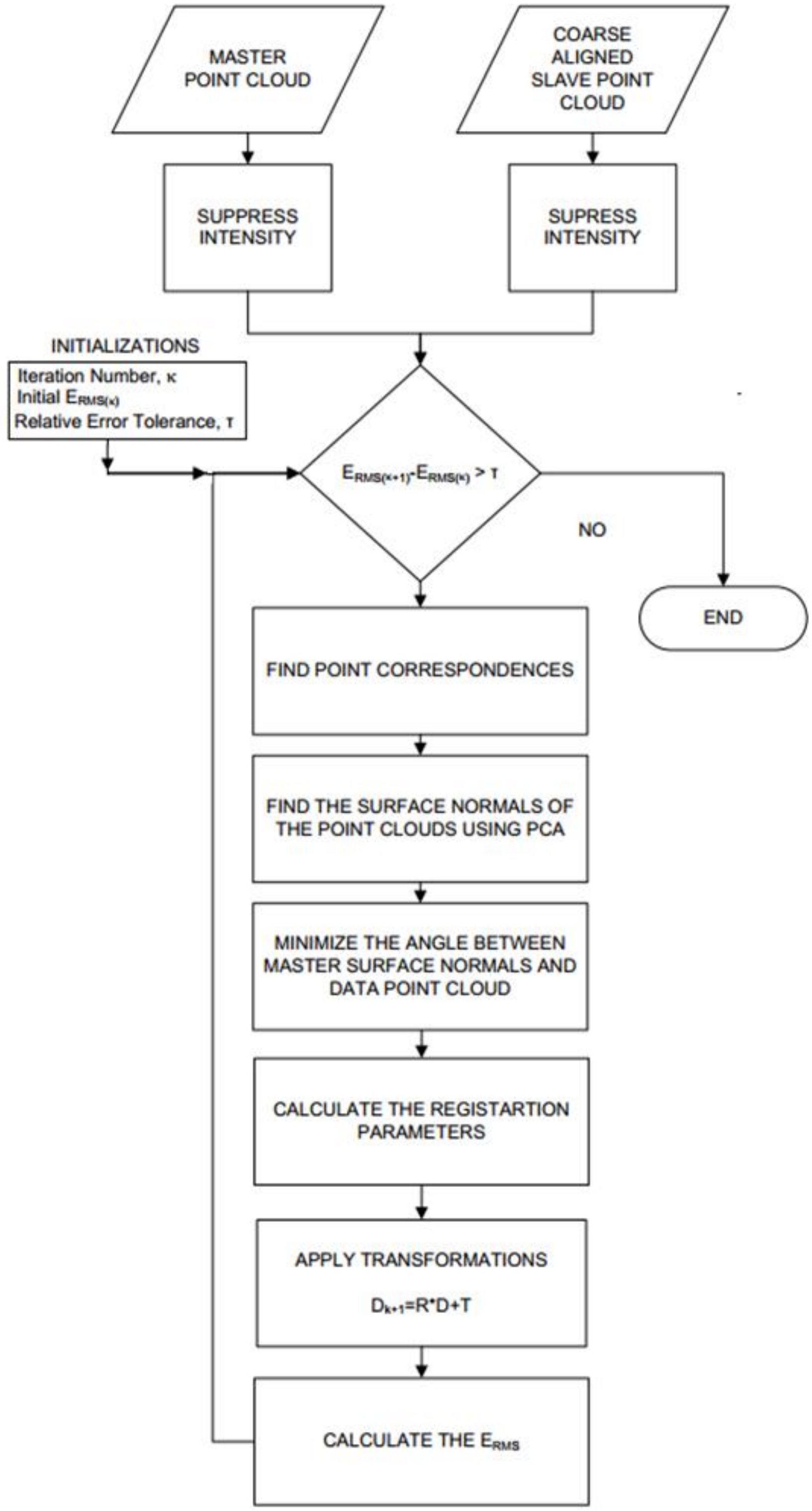

Figure 4: Fine registration – Phase-II

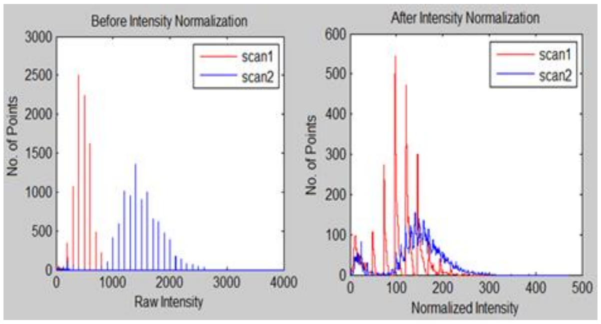

Figure 5: Concrete wall

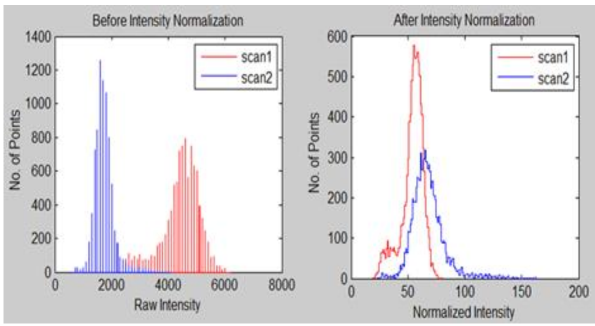

Figure 6: Brick wall

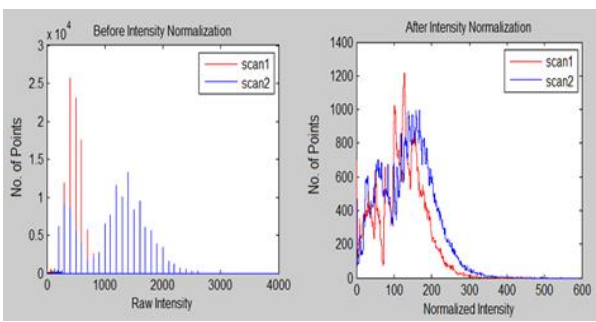

Figure 7: Plastic object

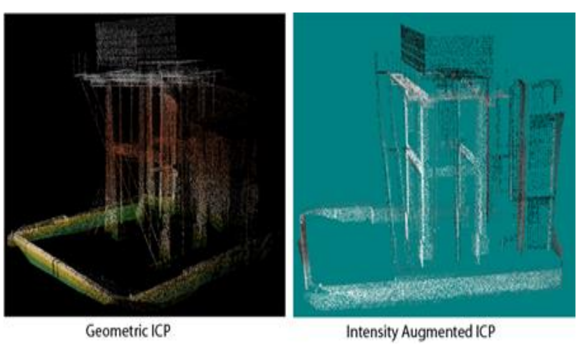

Figure 8: Data set I (Concrete wall)

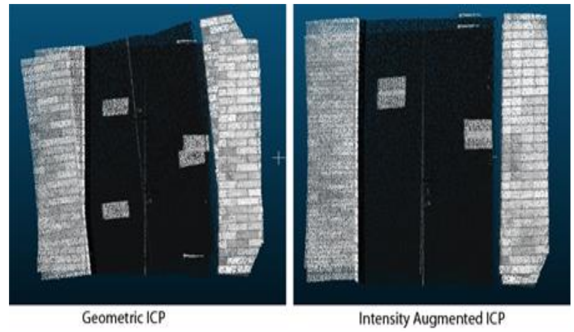

Figure 9: Data set II (Concrete wall)

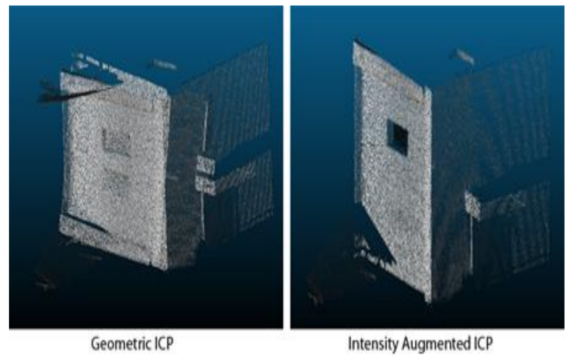

Figure 10: Data set III (Brick wall)

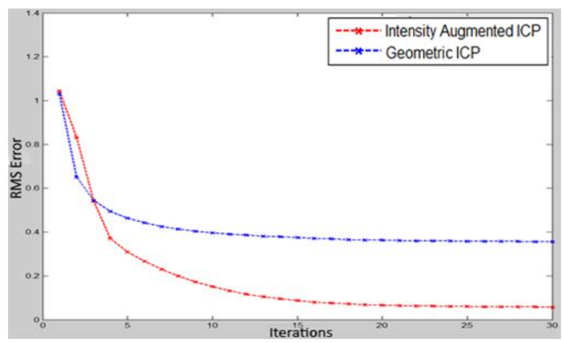

Figure 11: Convergence graph - ICP Vs IAICP for data set I

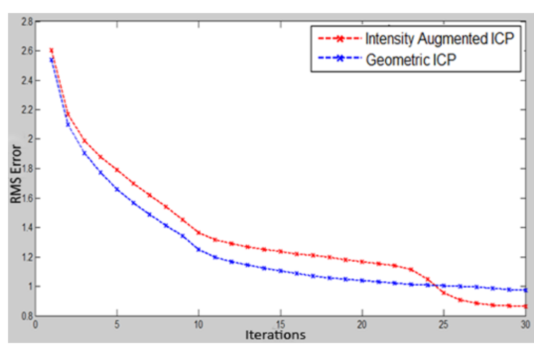

Figure 12: Convergence graph - ICP Vs IAICP for data set II

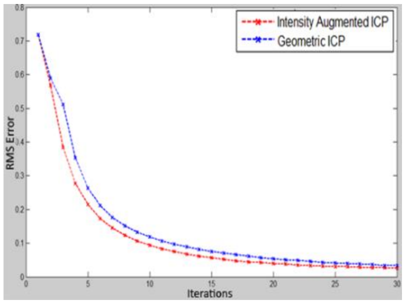

Figure 13: Convergence graph - ICP Vs IAICP for data set III

Table 2: Raw vs. normalized

Dataset	Raw	Normalized
Brick Wall-I	0.77	0.53
Brick Wall-II	2.31	0.61
Concrete Wall-I	1.39	0.43
Concrete Wall-II	0.83	0.13
Iron Door	0.43	0.44
Plastic Object	0.39	0.32

Table 3: ICP vs IAICP – RMS errors

Dataset	Geometric ICP	Intensity Augmented ICP
I	0.3563	0.0577
II	0.8976	0.8256
III	0.0326	0.0261

As shown by the results of data set II & III, despite comparable RMSE, it is important to note that in the case of geometric ICP the slave scan was inverted thereby providing absolutely incorrect registration. This is due to the fact that geometric ICP has converged at a local minimum. In the case of IAICP the registration is correct, which is basically due to the use of intensity information in the coarse registration process. The convergence graph shows that IAICP converges faster.

Discussions

Most commercially available software for LiDAR and Flash LiDAR (Lohani et al., 2013) surveillance are designed for manual registration, classification and segmentation (Sasidharan, 2012). The automatic registration process in commercial software is generally not found correct in geometrically confusing cases, as it may converge to a local minimum. The procedure adopted in practice is to collect a good number of control points and use these through similarities transform to provide initial condition to ICP. In the present paper, an Intensity Augmented ICP has been proposed, where first a coarse registration has been realized by using intensity along with geometric information through ICP. This process has potential to replace the manual selection of control points before proceeding to fine registration. In the present paper, the fine registration has been achieved by Point to Plane ICP. While performing IAICP the intensity of both scans should be normalized, as proposed in the present approach.

Conclusion

The paper has shown, using a few sample data sets, that the intensity normalization approach suggested is effective and brings the intensities of multiple scans to the same level, thereby facilitating their comparison. The paper has further shown, with scan data of a few sites, that how simple ICP can fail in geometrically confusing circumstances, while IAICP has the potential to converge to the global minima, as the fourth dimension added in ICP process provides additional information to locate distinctive features in both the scans. The proposed approach can be tested on more data and used in commercial software.

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Annexure **1:** Estimation Registration Parameter

Input:

Point set M with m
Point set D with n

Initialization:

Let p = number of spatial dimensions
Calculate μ_M and μ_D // Mean vectors of M and D data sets
Calculate Σ_{MD} // Covariance matrix of M and D data sets

Begin:

Calculate Singular Value Decomposition of Σ_{MD} (U, S, V)
Use Identity Matrix for S
If *rank* (Σ_{MD}) > p-1
Calculate the registration parameters as follows
$R(\omega, \phi, \kappa) = VSU^T$ // 3x3 Registration Rotation Matrix
$T(x, y, z) = \mu_D - R(\omega, \phi, \kappa)\,\mu_M$ // 3x1 Translation Matrix
Else *rank* (Σ_{MD}) ≤ p-1

$$S = \begin{cases} I & \text{if } det(U)det(V) = 1 \\ diag(1, 1, \ldots, 1, -1) & \text{if } det(U)det(V) = -1 \end{cases}$$

Calculate the registration parameters: $R(\omega, \phi, \kappa)$
And $T(x, y, z)$ using adjusted Identity Matrix
End

End

Output:

$R(\omega, \phi, \kappa)$ and $T(x, y, z)$ //Final registration Parameters

Annexure **2:** Iterative Closest Point (ICP) Algorithm

Input:

Master point cloud M with m number of points
Slave point cloud D with n number of points

Initialization:

- Set Number of Iterations, κ=0
- Set Rotation Matrix R as Identity Matrix
- Set Translation Matrix T with apriori translation vector
- Set Initial value for RMSE, E_{RMS}

Set Relative Error tolerance, ε

Begin

For

$D_{\kappa+1} = R_{ini} * D_\kappa + T$

While $(E_{RMS(K+1)} - E_{RMS(K)} \geq \varepsilon)$

- Find point correspondences using k-Nearest Neighbor search
- Compute the registration parameters using SVD (Algorithm 1)
- Apply Registration: $D_{\kappa+1} = R * D_\kappa + T$
- Calculate $E_{RMS(\kappa+1)}$
- Increment κ

End

End

End

Output:

Rotation Matrix, R
Translation Matrix, T