Alternative Approaches for Feature-Based Down-sampling of Irregular Point Clouds for Fine Registration

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ABSTRACT:
Due to the varying nature of acquired/derived 3D data from active/passive sensors, the fine registration of point clouds with non-uniform point density remains to be a challenging task. To address this challenge, two down-sampling procedures, which aim at improving the efficiency and accuracy of the ICPatch-based fine registration, are introduced in this paper. Specifically, the first approach is based on an adaptive down-sampling strategy to remove redundant points in areas with high point density while keeping points in lower density regions. The second procedure starts with the derivation of surface normal for the constituents of a given point cloud using their local neighborhoods. The derived surface normals are represented on a Gaussian Sphere. Then, a down-sampling procedure is achieved by removing points from detected peaks in the Gaussian Sphere. Experimental results from both simulated and real datasets are conducted to verify the feasibility of the proposed down-sampling procedures in providing reliable transformation parameters in the presence of random noise in the acquired point clouds. In addition, the derived experimental results also demonstrate that the implemented down-sampling can exceed the performance of some conventional fine registration approaches, which utilize either the original or uniformly down-sampled points, in terms of providing smaller RMSE values and faster convergence rate.

1. INTRODUCTION
Accurate three dimensional modelling of objects has become an important task for various applications, such as industrial site modelling, 3D documentation of historical monuments, urban planning, and several civilian and military applications. Currently, 3D reconstruction/representation of objects can be achieved through either active or passive remote sensing systems. Active sensors, such as laser scanners, directly provide precise and dense point cloud, which is properly scaled, along the scanned objects. In spite of the high point density of laser scanning data, break-lines are not usually well defined by such data. The derived laser-based point cloud usually lacks spectral information (especially when dealing with data collected by laser scanners onboard mobile platforms). On the other hand, passive sensors such as digital frame cameras can be incorporated for 3D reconstruction while providing spectral attributes for the derived coordinates. Such semantic attributes would allow for the derivation of better and more reliable information pertaining to the reconstructed objects. However, the main challenge in deriving 3D information from passive sensors is feature matching in overlapping imagery (i.e., the automated identification of conjugate features in the involved images). Considering the complementary characteristics of derived 3D data from active and passive sensors, the geospatial research community has advocated the integration of point clouds from these data acquisition modalities (González-Aguilera et al., 2009). One should note that effective integration of such derived data depends on their alignment relative to a common reference frame, which is known as the registration problem.

The registration of 3D point clouds involves the estimation of the 3D Helmert transformation parameters (i.e., scale factor, three translations, and three rotation angles) relating the reference frames of the different point clouds. Depending on the accuracy of estimated transformation parameters, current registration procedures can be categorized into either coarse or fine registration techniques (Matabosch et al., 2005). Coarse registration is usually used to establish rough alignment between the involved point clouds (He and Habib, 2016). Fine registration, on the other hand, starts from coarsely-aligned point clouds to achieve more precise alignment of the involved datasets. The most commonly used approach for fine registration is the Iterative Closest Point (ICP), where the transformation parameters are iteratively refined by generating pairs of corresponding points and minimizing point-to-point distances (Besl and McKay, 1992; Chen and Medioni, 1991). Due to the irregular nature of point clouds, point-to-point correspondence cannot be always assumed. Therefore, different variants of the ICP have been introduced. For example, the Iterative Closest Patch (ICPatch) utilizes points in one point cloud and triangular patches in another point cloud as the registration primitives (Habib et al., 2010a). Instead of minimizing the point-to-point distance, the IPCPatch approach is implemented by minimizing the sum of the squared normal distances between conjugate point-patch pairs. Although current ICP and its variants (e.g., IPCPatch) have demonstrated their feasibility in providing reliable point clouds registration, they do not consider the varying characteristics of 3D point clouds arising from active and passive sensors onboard various platforms. For example, the point density acquired from airborne laser scanners (ALS) is usually in the range from 1 to 40 pts/m2 (Hyyppä et al., 2009), which is much lower than that for a terrestrial laser scanner (TLS) and mobile terrestrial laser scanner (MTLS) data. In practice, such varying nature might lead to unreliable estimation of the transformation parameters. The potential challenges associated with the ICP-based registration for 3D point clouds derived from active and passive sensors can be summarized as follows:

1. The derived image-based/laser-based point clouds usually include excessive number of points. Therefore, for these

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datasets, the conventional ICP-based registration, which utilizes the entirety of the available points, is usually very time-consuming. For example, there are usually thousands of points acquired along a given planar feature within a high point density area. However, only a few of them are required to represent a reliable planar surface, whereas the remaining points are redundant.

2. Due to the nature of the utilized sensors, the acquired point clouds usually do not have a uniform point density. For example, the point cloud acquired by a TLS usually have a higher point density close to the scanner. Such variations in point density will negatively impact the quality of the registration procedure as they might lead to over-weighting for points in high density areas.

The existing body of literature has demonstrated that point cloud down-sampling will have a significant impact on improving the efficiency and accuracy of the fine registration. Turk and Levoy (1994) proposed a simple down-sampling strategy for the ICP, where the involved point clouds is randomly down-sampled. In each iteration of the ICP, a set of random points are utilized. However, such simple down-sampling strategy does not consider the local surface characteristics or the local point density variation within the involved point clouds, and it only improves the efficiency of the registration by reducing the number of utilized points. Weik (1997) investigated the utilization of points with high intensity gradient to improve the accuracy of the ICP-based registration. However, in his work, color or intensity information is required. A most recent down-sampling strategy for the ICP is proposed by Rusinkiewicz and Levoy (2001). In their work, a normal space, which is based on the surface normal of each point, is first generated. Then, points are selected in the normal space to make sure variation among normal vectors is as large as possible. However, some “unreliable” points, such as points from trees and other vegetation, may be utilized for the estimation of transformation parameters. This would lead to an unstable alignment of the point clouds.

Therefore, this research is dedicated to addressing the above-mentioned challenges for point cloud fine registration – namely, the excessive number of points, and the varying point density - by presenting two alternative approaches. Different from current point cloud down-sampling techniques (e.g., random-based down-sampling), the introduced approaches consider the physical characteristics of the encompassing surfaces and the distribution of point clouds in 3D. More specifically, the first approach is based on an adaptive down-sampling strategy to remove redundant points in areas with high point density while keeping points in lower density regions. The second procedure starts with deriving surface normal, which can be presented on a Gaussian Sphere, of a given point cloud using their local neighborhoods. Then, down-sampling is achieved by removing points from peaks detected in the Gaussian sphere. It is worth mentioning that in the proposed two approaches, only points from planar regions will be identified and utilized for the fine registration. The motivation behind using planar points is that rough/linear points may have negative impacts on the fine registration as either point-to-point or point-to-patch correspondences cannot be assumed. Finally, a comparative analysis, which comments on the computational efficiency and the registration quality, will be carried out in this research to evaluate the performance of the two proposed approaches.

In the remainder of this paper, the details of the two introduced approaches for point cloud fine registration are first introduced. Afterwards, a comparative analysis, which comments on the computational efficiency and the registration quality, is conducted on both simulated and real datasets. Finally, drawn conclusions and recommendations for future work are introduced.

2. SPATIAL INFORMATION-BASED DOWN-SAMPLING METHODOLOGIES

In this research, a fully automated workflow, which incorporates the two proposed down-sampling approaches, is implemented for improving the fine registration relating two point clouds (i.e., the aligned and reference point clouds). As shown in Figure 1, the proposed workflow includes three steps. In the first step, the aligned point cloud is initially classified as planar, linear/cylindrical, and rough points based on their local neighborhoods. Then, the two proposed approaches are conducted on points from planar regions to reduce the data size. Finally, the down-sampled planar points are introduced to an Iterative Closest Patch (ICPatch) algorithm for fine registration (Habib et al., 2010b).

Figure 1. Workflow of the proposed methodologies

2.1 Localization Neighborhood Characterization

Since the proposed down-sampling procedures are only applied on points within planar regions, a local neighborhood characterization is initially implemented for identifying the points that belong to planar, linear and cylindrical, and rough features. The local neighborhood characterization can be achieved through an eigenvalue analysis for a given point \(p_o\) using its \(n\) nearest neighbors. The eigenvectors represent the orientation of the neighborhood in the 3D space, while the eigenvalues define the extent of the neighborhood along the directions of their corresponding eigenvectors. For a planar neighborhood, one of the eigenvalues will be quite small when compared to the other two (See Figure 2). Once the local planar neighborhood is classified, the local point density of the identified planar point can be derived. The mathematical model for the local point density estimation is presented as Equation 1.

\[
LPD\left(\frac{p_{max}}{m^2}\right) = \frac{n+1}{n \sigma^2}
\]

(1)

Where, \(n\) is the number of points within the local neighborhood, and \(r_n\) is the distance between the point \(p_o\) and its \(n^{th}\) farthest neighbor.
2.2 Point Cloud Down-Sampling

Now that the local neighborhood characterization is completed, the two proposed approaches can be adopted to reduce the number of points along planar surfaces. In this research, the first approach is based on an adaptive down-sampling procedure (Al-Durgham, 2014; Lin, 2016). The second approach, on the other hand, is achieved by removing points from detected peaks in a Gaussian Sphere, which is generated from the surface normal derived from the local neighborhood characterization process.

2.2.1 Adaptive Down-Sampling

The conceptual basis of the adaptive down-sampling is to achieve a desired point density through the probability-based test in Equation 2.

\[ \delta = \frac{1}{d_i} = \begin{cases} \geq r, & \text{maintain} \\ \text{else}, & \text{eliminate} \end{cases} \quad (2) \]

Where, 
\( d_i \) is the local point density within the \( i \)th point local neighborhood in pts/m\(^2\), and 
\( r \) is a random number that is picked from a uniform distribution in the range [0, 1].

According to Equation 2, when the local point density (\( d_i \)) of a point is below a desired point density (\( i \)), the point will be maintained in the down-sampled point cloud since the test value (\( d \)) will be larger than 1. On the other hand, Since the range for the random number (\( r \)) generated using a uniform distribution in the range of [0, 1], when the local point density is larger than the desired point density, the point has a probability of (1 - \( d \)) to be removed. Interest readers can refer to Lin (2016) for more details.

2.2.2 Gaussian Sphere-Based Down-Sampling

Alternatively, motivated by the fact that points within the same planar region have similar surface normals, the second approach starts with the derivation of surface normal for the constituents of a given point cloud. In this research, the surface normal of points along planar surfaces are derived through the local neighborhood characterization, which has been introduced in Section 2.1. Then, the derived surface normals for all those points that are classified as planar features are represented on a Gaussian Sphere. Afterwards, the down-sampling is achieved by removing points from detected peaks in the Gaussian Sphere. Due to the utilization of the Gaussian Sphere, this approach will be denoted here forth as the “Gaussian Sphere-based Down-sampling”. In the remainder part of this section, the Gaussian Sphere-based approach is introduced through three steps, which can be summarized as: Gaussian Sphere generation, brute force-based peak detection, and Gaussian Sphere-based point removal.

Gaussian Sphere Generation: With the purpose of down-sampling points that have similar surface normal, a representation that groups points into a different domain is required. Gaussian sphere, also known as the Extended Gaussian Image (EGI) is a mapping of the surface normals of a specific object onto a sphere of unitary radius to represent the orientation attribute (Horn, 1984). For any point cloud data, the EGI could be established by projecting the surface normal estimated for the constituents of a point cloud to a specific sphere. Figure 3 shows a sample Gaussian sphere created from a point cloud dataset.

Brute Force-based Peak Detection: In order to remove redundant points from each peak on the Gaussian Sphere, the identification of existing concentration areas on the Gaussian Sphere is required. A brute-force peak detection approach, which traverses the Gaussian Sphere point cloud (Lari and Habib, 2014), is adopted in this research. More specifically, this approach starts with constructing a KD-tree structure for all derived surface normals, which can be represented on the Gaussian Sphere. As shown in Figure 4, a threshold of 5° solid angle is then pre-defined to determine the search radius for peak detection. Afterwards, each of the involved points is traversed to retrieve the one with the maximum number of neighboring points within the pre-defined search radius on the Gaussian Sphere for peak detection. Once a peak is identified, the detected point as well as all points fallen into its neighborhood as determined by the 5° solid angle are eliminated from the KD-tree structure. Such peak detection and elimination process will be repeated until the largest number of points within a given neighborhood is smaller than a predefined threshold.

Figure 2. Eigenvalue analysis of a planar neighborhood

Figure 3. A sample image of a Gaussian Sphere

Figure 4. A 5° solid angle on Gaussian Sphere is predefined to determine the search radius for peak detection
Gaussian Sphere-based Point Removal: Before applying the down-sampling process, one should note that a single peak detected on the Gaussian Sphere may correspond to several spatially-disconnected planar regions. In order to identify these spatially-disconnected planar regions, the proposed point removal strategy starts with a Euclidean distance-based connected component approach, which aims at grouping points into several disconnected planar surfaces based on point-to-point Euclidean distances. As shown in Figure 5, points i and j are grouped into the same planar surface P as the distance \(d_{ij}\), which denotes the distance between the two given points (i.e., \(i\) and \(j\)), is less than a pre-defined threshold \(d\). On the other hand, point \(k\) cannot be grouped into \(P\) since the distance \(d_{ik}\) exceeds the threshold. Now that the connected component procedure is completed, a reduction percentage is applied on each group to remove redundant points and maintain a maximum number of points for each of the detected peaks on the Gaussian Sphere. Different from the adaptive down-sampling approach, the Gaussian Sphere-based point removal does not rely on the estimated local point density.

\[ d_{ij} < d \text{ (Accepted)} \]

\[ d_{ik} > d \text{ (Rejected)} \]

Figure 5. Sample image to demonstrate Euclidean distance-based connected component

2.3 ICPatch Registration

Once the down-sampling procedure is finalized, the ICPatch approach is implemented for the precise alignment of the involved point clouds. In this research, the ICPatch registration is performed between the \(aligned\) point cloud, which has been down-sampled through the introduced approaches, and the \(reference\) data. Instead of point-to-point correspondence, the geometric primitives chosen for the ICPatch registration are points and triangular patches (Habib et al., 2010). Therefore, for any two overlapping surfaces, one of the point clouds is kept as is, and the other one is converted to a set of triangular patches. Conventionally, a Triangulated Irregular Network (TIN) is usually utilized for the patch generation. However, the generation of TIN can be only adopted in 2D space. Therefore, in this research, instead of using the TIN to define the patches, the point-to-patch correspondences are established by searching for the three closest points of each query point. Then, the co-planarity constraint is implemented using all derived point-to-patch correspondences to solve for the transformation parameters between the two involved point clouds. In this research, query points are selected in the \(aligned\) point cloud, and the corresponding patches are defined in the \(reference\) data.

3. EXPERIMENTAL RESULTS

Experimental results from simulated and real datasets have been conducted to investigate the feasibility of the two proposed down-sampling procedures in providing reliable transformation parameters for the fine registration of 3D point clouds.

3.1 Simulated Dataset

There are two objectives for the experimental testing with simulated dataset. The first objective is to evaluate the impact on the estimated transformation parameters when adding noise with different magnitude to the simulated point cloud. In this research, the ability of the tested approaches to deal with introduced noise is evaluated by gradually increasing the noise level to a standard deviation of ±0.05 m. Only the two proposed approaches are tested for the first objective. The second objective, on the other hand, is to evaluate the performance of the implemented down-sampling procedures against two commonly adopted strategies for the ICPatch registration, including using: 1) all possible points and 2) a set of randomly down-sampled points. More specifically, for the simulated dataset, a set of five planes with different orientation have been generated (See Figure 6). The ground coverage of the simulated dataset is 20 m by 20 m, and the height range is 25 m. The maximum point density of the simulated planes is 1600 pts/m², while the minimum point density is 25 pts/m². Then, a set of pre-defined 3D-Helmert transformation parameters, Table 1, is applied to the simulated points to generate another point cloud established in a different coordinate system. In this research, the point cloud, which is transformed to a different coordinate system, is utilized as the \(reference\), while the original simulated points are considered as the \(aligned\) dataset. Figure 6 illustrates both the \(reference\) and \(aligned\) point clouds.

<table>
<thead>
<tr>
<th>(T_x) (m)</th>
<th>(T_y) (m)</th>
<th>(T_z) (m)</th>
<th>(s)</th>
<th>(\omega^\circ)</th>
<th>(\phi^\circ)</th>
<th>(k^\circ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.15</td>
<td>-0.38</td>
<td>0.27</td>
<td>1.0</td>
<td>3.5</td>
<td>-2.8</td>
<td>1.6</td>
</tr>
</tbody>
</table>

Table 1. The 3D-Helmert transformation parameters relating the coordinate systems of the simulated \(reference\) and \(aligned\) datasets

3.1.1 Simulated Dataset Results

Table 2 illustrates the absolute rotation and translation differences between the estimated and true transformation parameters at each given noise level using the two proposed approaches. In order to compare these two approaches with the other two commonly adopted strategies (i.e., using a set of randomly selected points or all possible points), the convergence of each estimated transformation parameter as well as the derived RMSE values (i.e., the RMSE of point-to-patch normal distances in ICPatch) for each conducted tests are illustrated in Figure 7. It is worth noting that this comparison is only conducted on the simulated dataset with a ±0.05 m noise level. One should also note that since the number of points may have significant impact on the fine registration, in this research, the number of points derived from the adaptive down-sampling is used as the reference number. Then, the reduction percentage of Gaussian Sphere-based and random down-sampling is accordingly adjusted to ensure a compatible number of query points for the ICPatch registration. In this experimental test, the desired local point
density for the aligned point cloud is set to 20 pts/m². Table 3 presents the number of points utilized in each of the conducted tests. To be specific, the total number of points in the aligned dataset is reported in Column 2. Since both adaptive and Gaussian Sphere-based down-sampling are conducted on points along planar surfaces, the number of planar point features, which are derived from the local neighborhood characterization process, is presented in Column 3. The number of points utilized for ICPatch is illustrated in Column 4.

Table 2. Absolute rotation and translation differences for various noise values using the adaptive and Gaussian Sphere-based down-sampling

<table>
<thead>
<tr>
<th>Noise (m)</th>
<th>ΔTX (m)</th>
<th>ΔTY (m)</th>
<th>ΔTZ (m)</th>
<th>Δϕ (°)</th>
<th>Δθ (°)</th>
<th>Δκ (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>0.002</td>
<td>0.001</td>
<td>0.002</td>
<td>0.003</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>0.02</td>
<td>0.001</td>
<td>0.002</td>
<td>0.004</td>
<td>0.005</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>0.03</td>
<td>0.011</td>
<td>0.010</td>
<td>0.012</td>
<td>0.011</td>
<td>0.002</td>
<td>0.010</td>
</tr>
<tr>
<td>0.04</td>
<td>0.011</td>
<td>0.011</td>
<td>0.014</td>
<td>0.010</td>
<td>0.008</td>
<td>0.019</td>
</tr>
<tr>
<td>0.05</td>
<td>0.003</td>
<td>0.022</td>
<td>0.006</td>
<td>0.005</td>
<td>0.019</td>
<td>0.011</td>
</tr>
</tbody>
</table>

Table 3. The number of points utilized in the four conducted tests: 1. adaptive down-sampling, 2. Gaussian Sphere-based down-sampling, 3. random down-sampling, and 4. using all points.

Table 3. The number of points utilized in the four conducted tests:

<table>
<thead>
<tr>
<th></th>
<th>Number of points in the aligned dataset</th>
<th>Number of planar point features</th>
<th>Number of down-sampled points for ICPatch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adaptive</td>
<td>10,709</td>
<td>99,977</td>
<td>3,944</td>
</tr>
<tr>
<td>Gaussian Sphere</td>
<td>10,709</td>
<td>99,977</td>
<td>3,944</td>
</tr>
<tr>
<td>Random</td>
<td>10,709</td>
<td>N/A</td>
<td>3,944</td>
</tr>
<tr>
<td>All Points</td>
<td>10,709</td>
<td>N/A</td>
<td>10,709</td>
</tr>
</tbody>
</table>

Closer inspection of the derived results in Tables 2 and 3, and Figure 7 reveals the following:

1. For simulated dataset with gradually increasing the noise level to a standard deviation of ±0.05 m, the maximum absolute rotation and translation errors derived from the two proposed down-sampling errors are 0.019° and 0.031°, and 0.0022 m and 0.0025 m, respectively (highlighted in Table 2). This result indicates that both the adaptive and Gaussian Sphere-based down-sampling provide accurate estimate for the transformation parameters.

2. Compared to the two commonly adopted strategies – random down-sampling or using all points, the two implemented procedures have much faster convergence rate. This result demonstrates that the two implemented down-sampling approaches can be more efficient for the fine registration.

3. The ICPatch registration using either a set of randomly selected or all possible points demonstrate a similar performance in terms of their convergence rate. This is due to the fact that the random down-sampling does not change the distribution of the utilized point clouds (i.e., after applying the random down-sampling, there are more points in the high point density area while less points in the low point density regions).

4. In spite of the comparable RMSE values of the point-to-patch normal distance, the proposed adaptive down-sampling demonstrates better convergence rate on both estimated translation and rotation parameters when comparing to the Gaussian Sphere-based approach. This result indicates that the proposed adaptive down-sampling can be more helpful for the fine registration since it requires less iterations to converge.

3.2 Real Dataset

One real dataset, which is acquired at the vicinity of a building, is utilized for the experimental test. For this real dataset, two point clouds with a total number of 66,541 (reference dataset) and 143,779 (aligned dataset) points are acquired by a Leica HDS 3000 static laser scanner. Similar to the experimental tests for the simulated dataset, both the two proposed approaches and the two commonly adopted strategies are conducted on the real dataset. For the adaptive down-sampling approach, the desired local point density is set to 20 pts/m². In this experimental test, a total number of 23,059 points are maintained in the aligned dataset after conducting the adaptive down-sampling. Then, the reduction percentages for the Gaussian Sphere-based and random down-sampling are accordingly adjusted to ensure a compatible number of points used in the ICPatch registration. Figure 8 illustrates the two utilized real laser point clouds.
3.2.1 Real Dataset Results

The experimental results derived from the real dataset is presented in Table 4. To be specific, columns 2, 3, and 4 of the table show the number of points utilized in each of the conducted test. Besides, the derived RMSE values of the point-to-patch normal distance and the total execution time for each of the conducted tests are reported in Columns 5 and 6 of Table 4, respectively.

Looking into these results, one can note that, for this real dataset, the random down-sampling has the largest RMSE value of 0.071 m, while the adaptive down-sampling demonstrates the smallest RMSE value of 0.044 m. Compared to the adaptive down-sampling, the Gaussian Sphere-based down-sampling has a similar performance in terms of the derived RMSE value. However, it takes the longest time to complete the whole procedure since we use a brute-force approach for the peak detection, which is quite inefficient and time-consuming. Considering both the execution time and the derived RMSE values, one can conclude that the adaptive down-sampling is the best option for this real dataset since it is capable of providing a small RMSE value while completing the whole procedure within a relative short execution time.

<table>
<thead>
<tr>
<th>Number of points in the aligned dataset</th>
<th>Adaptive Sampling</th>
<th>Gaussian Sphere</th>
<th>Random Sampling</th>
<th>All Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>143,799</td>
<td>143,799</td>
<td>143,799</td>
<td>143,799</td>
<td></td>
</tr>
<tr>
<td>Number of planar point features</td>
<td>12,7862</td>
<td>12,7862</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of down-sampled points for ICPatch</td>
<td>23,059</td>
<td>23,059</td>
<td>23,059</td>
<td>143,799</td>
</tr>
<tr>
<td>RMSE (m)</td>
<td>0.044</td>
<td>0.048</td>
<td>0.071</td>
<td>0.060</td>
</tr>
<tr>
<td>Execution time (sec)</td>
<td>113.27</td>
<td>895.61</td>
<td>34.52</td>
<td>193.56</td>
</tr>
</tbody>
</table>

Table 4. The experimental results of the four tests 1. adaptive down-sampling, 2. Gaussian Sphere down-sampling, 3. random down-sampling, and 4. using all points for the real dataset

4. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

In this research, we introduced two down-sampling procedures for the registration of 3D point clouds with non-uniform point density. The first procedure utilizes an adaptive down-sampling strategy to remove redundant points in areas with high point density while keeping the points in lower density regions. The second procedure starts with the derivation of surface normal for each point. Then, the surface normal are projected on a Gaussian sphere. Afterwards, down-sampling is achieved through removing points from peaks detected in the Gaussian sphere. Experimental results have shown that both adaptive and Gaussian Sphere-based down-sampling procedures are capable of providing reliable estimate of the transformation parameters in the presence of random noise in the utilized point clouds. It is worth mentioning that for the Gaussian Sphere-based down-sampling procedure, the peaks are detected through a brute-force approach with a fixed search radius. This implementation can be time-consuming and inefficient. Therefore, our future work will focus on the improvement of peak detection in the Gaussian Sphere. Rather than adopting the brute-force strategy for peak detection, a more efficient search strategy will be used. Then, the utilization of an adaptive search radius, which can be derived while considering the local noise level, will be investigated.

REFERENCES


