

Large Scale 3D Scene Reconstruction with Improved Registration of Laser Range Data

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Abstract

The paper proposes two approaches to improve the Iterative Closest Point (ICP) algorithm in the registration of large scale range data obtained by a Velodyne LIDAR at different locations in an outdoor environment. The first proposed approach discards points that cannot be matched in the datasets during the registration process to prevent errors from these points from affecting the results. The second approach extracts feature points that are representative of the datasets to perform the registration process and similarly preventing mismatching points from affecting the results. Experiments show that both approaches perform better than the original ICP algorithm.

Key Words: 3D Reconstruction, Range Data, LIDAR, Iterative Closest Point, ICP

1. Introduction

Recent technology advancements have allowed three dimensional reconstructions of objects and scenes to be increasing popular and accurate. Applications of 3D technology in areas such as entertainment, historical preservations, reverse engineering and many others have greatly increased in number. Many 3D reconstruction methods have been developed to provide better resolutions and accuracy to cater for the wide range of applications. Nevertheless, there are still many issues and rooms for improvement in 3D reconstruction, including the reconstruction accuracy, speed, and resolutions.

In this paper, we focus on the large scale 3D reconstructions of building, or of scenes using a LIDAR (Light Detection and Ranging) device [1–4]. The device has 64 laser emitters and receivers. It rotates at 5–15 Hz to acquire surrounding range data in real-time, with 0.09 degree angular resolution and 26.8 degree vertical field of view. The device is placed at various locations within the scene to acquire 360 degree 3D reconstructions of the surrounding at each location. The 3D data obtained at

each location need to be registered and combined to form a detailed 3D model of the scene.

The paper proposes a method to achieve the registration of the 3D data acquired by the LIDAR at different locations. The method first performs a rough alignment of the datasets using the Iterative Closest Point (ICP) algorithm. Once the initial parameters for alignment have been obtained, we then perform finer registrations of the dataset to locate the optimal alignment positions. The datasets are also examined to remove redundant or unreliable points which might affect the fused result. Finally, integration of the processed 3D datasets is performed to merge the data from each different location and obtain a 3D model of the scene. Experimental results are provided to demonstrate the effectiveness of the approach in providing more accurate and detailed 3D model of scene.

2. Preprocessing and Initial Registration

2.1 Range Data Acquisition

The LIDAR device is placed upon an elevated platform at the center of the scene to be reconstructed. The device rotates at frequencies of up to 15 Hz to acquire

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raw range data of the scene. Figure 1 shows the hardware setup for acquiring for 3D scene reconstruction.

The acquired range data are contained in series of data packets which need to be divided and parsed to extract the data for each 360 degree scan of the scene. Since the LIDAR rotates at 5–15 Hz, multiple scans are acquired at each location. To facilitate alignment and simplify processing, we only use one 360 degree scan at each location and discard repeated scans. Although in future work, the repeated scans may be utilized to improve the resolution of the reconstruction.

Figure 2(a) shows the top view of a scene to be reconstructed. The scene is taken in the corridors of a building. The LIDAR device is moved along the corridor to reconstruct the building structure. Figure 2(b) shows examples of scans at different locations. The two circles indicate the centers of the locations where data are acquired. Points in the two different datasets are shown in different colours. Note that these two datasets have already been registered for demonstration purposes.

2.2 Removal of Boundary Points

According to the specifications of the device, the effective range of the LIDAR device is 0.9 to 120 m. Points that are outside the effective range are likely to be erroneous. Figure 3 shows a scan of the scene with the points outside the effective range shown in red. In each

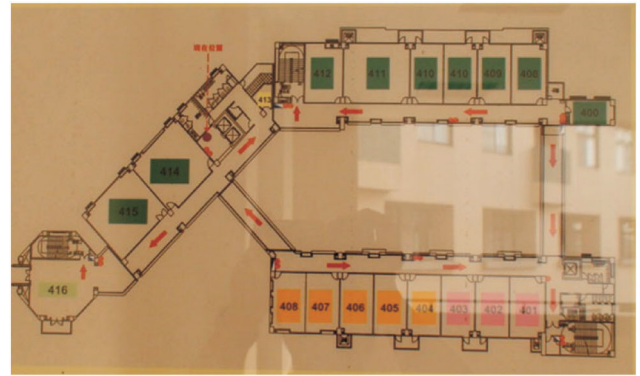


Figure 1. Hardware setup of the LIDAR for 3D scene reconstruction.

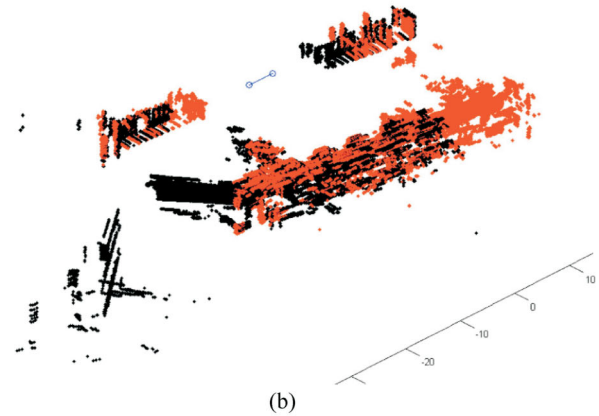
3D scan of the scene, such points are removed before further steps are performed.

2.3 Initial Registration of Data

The iterative closest point (ICP) algorithm is first



(a)



(b)

Figure 2. (a) Top view of the scene to be reconstructed. (b) An example of scans of the scene from two different locations.

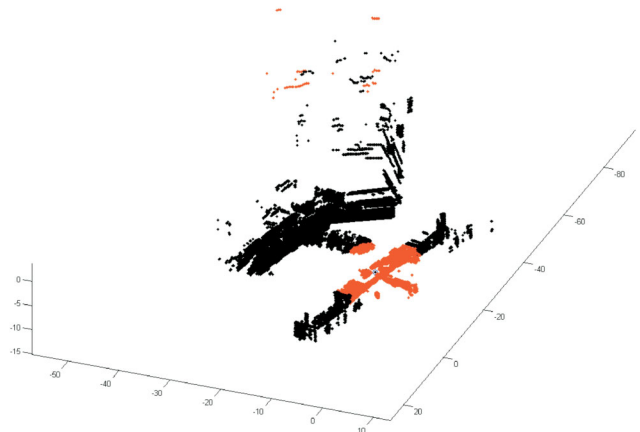


Figure 3. Points removed from a scan of the scene are shown in red.

proposed in 1992 by Besl and McKay [5]. It is a common approach for the registration of rigid 3D points. The main idea of the method is to minimize the distances between points in datasets that are to be registered.

We start with two sets of data acquired at adjacent locations, similar to the two datasets shown in Figure 2. Let $X_0 = \{x_{0i}\}$ and $X_1 = \{x_{1i}\}$ represent the points in the first and the second of a series of datasets, where x_{0i} and x_{1i} are 3D points represented in Cartesian coordinates. Using the ICP algorithm, we can obtain a transformation matrix, such that a point x_{0i} can be matched to a closest point x_{1i} in the other dataset. The equation below is minimized to obtain the transformation matrix.

$$f(R, p) = \sum_{i=1}^n \|Rx_{0i} + p - x_{1i}\|^2 \quad (1)$$

In (1), R represents the rotational matrix and p represents the translation vector required to align dataset X_0 to X_1 . An average error is given by dividing (1) by the number of points in the dataset. The process is repeated iteratively until the average error is below a certain threshold, at which time, the transformation obtained is theoretically the transformation required to align datasets X_0 and X_1 .

Once the transformation has been found, it is stored in a pre-processing matrix T_1 , which is applied to the subsequent dataset before it is used to calculate the next set of transformations. The algorithm then moves along to the next set of data X_2 and aligns the next dataset with the previous dataset X_1 , obtaining another transformation T_2 , which is then concatenated with T_1 to give a new, combined transformation to move the subsequent dataset into position before registration. The process is repeated until all datasets are registered.

Suppose the transformation acquired to register dataset, X_{i-1} , and the next datasets X_i is given by T_i , the transformations applied to a new dataset X_{i+1} to move it to a position close to the previous datasets is shown in (2), where X'_{i+1} is the shifted dataset of X_{i+1} ,

$$X'_{i+1} = T_1 T_2 \dots T_i X_{i+1} \quad (2)$$

The pre-processing matrix $T_1 T_2 \dots T_i$ is the concatenation of all transformation matrices up to T_i . A loop is

used to perform the above said process. Details of the steps within the loop are illustrated in Figure 4.

After the initial registration loop, the rough displacement between adjacent locations can be obtained. Factors affecting the accurate calculation of the displacement include occlusion and the fact that the range data are not acquired in fixed intervals. Therefore, it is impossible to find a transformation that will align two dataset exactly, since the points in two datasets are almost never sample from the same position within the scene.

Figure 5 shows a section of the result of applying the alignment found in this stage to the different dataset, the different colours represents points from different datasets. In Figure 5, while the transformation between successive datasets might be optimal in the sense that it provides the minimal differences between the points, the

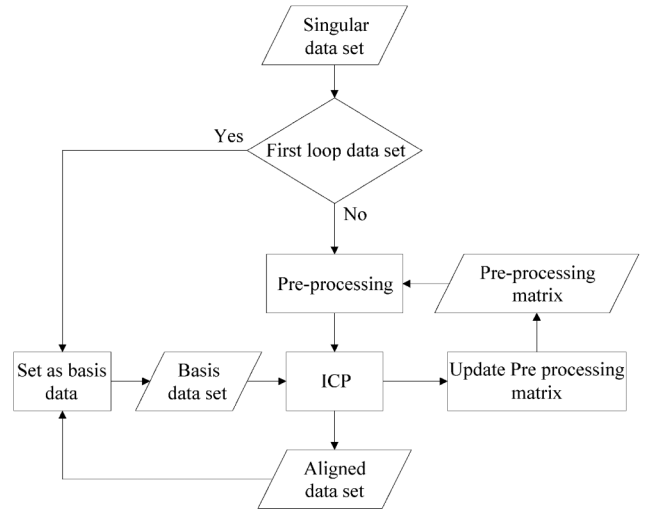


Figure 4. Flowchart of the ICP registration loop.

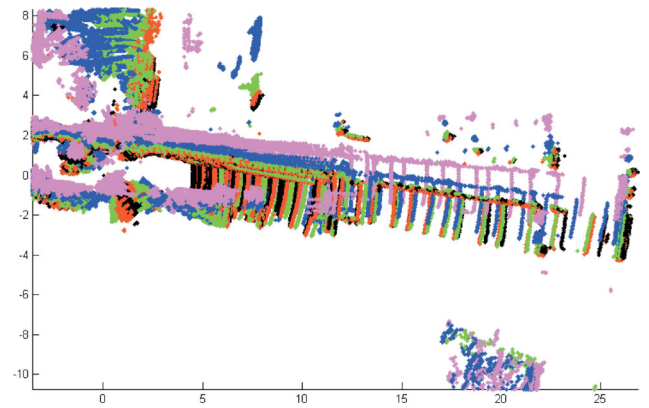


Figure 5. Accumulated errors between registered datasets.

datasets become less well aligned over time due to accumulated errors from previous alignments. Instead of perfectly overlapping each other, the datasets become further apart. The cause of this problem is that while some points are present in one dataset, these points are not guaranteed to be in the next dataset. Hence the mismatched points cause errors in the ICP algorithm and affecting the resultant registration.

The next section discusses how we dealt with this problem to achieve registration between the datasets.

3. Improved Registration Methods

3.1 Improving Alignment by Rejecting Mismatching Points

Several possible approaches to improve the registration between two datasets have been investigated. Most approaches suggest excluding points that do not have good match properties, such that they will not contribute errors and affect the final result [6–10]. After some experiments, we have found that by excluding points that are within a threshold of worst matching results can effectively improve the results of registration.

Therefore, by observing the differences, we can determine which points are less likely to be matched. These may be the points that are present in one dataset and absent in the other dataset. As a result, these points will have relatively large differences when calculated by (1). By setting a threshold for elimination, we can locate points that have the top $n\%$ highest differences and exclude them from further iterations of the loop. A common threshold for elimination is the top 10% [6]. We have performed experiments with threshold ranging from 1% to 40%. However, fixed threshold is unsuitable for our application because it offers little flexibility for dealing with the wide range of scene that we wish to reconstruct. In addition, it has been found that although faster convergence can be achieved with higher elimination threshold, since fewer points are taken into consideration, the aligned results are less satisfactory because there is an under representation of the overall scene structure. To improve upon the previous approach, we have used a dynamic rejection threshold that will be adjusted according to the convergence of the algorithm to provide better flexibility, as well as improved registrations between the datasets.

The proposed approach is as follows. The datasets are initially aligned as discussed in the previous section. Once an optimal transformation has been calculated for the dataset and further iterations are not significantly improving the results, we check to see if a better registration can be achieved by dropping the worst matching points. If so, the algorithm continues to perform registration with subsets of the initial datasets. The process is repeated until a maximum threshold has been reached, at which point, the algorithm checks all possible calculated results and determines the optimal transformations for the datasets. Figure 6 shows the described process.

In actual applications, the threshold for rejection is set to 0% initially. Once the datasets have been aligned to a stage where the total difference is below a set value, the rejection threshold is raised by 5%, such that the worst matching 5% of the points are left out of the algorithm in the next iteration. The algorithm continues and checks the total difference between the datasets for the next occasion to raise the threshold. The process is repeated until a maximum threshold has been reached. In our case we set the maximum threshold to 40%, since that is already a significant amount of points to leave out in the registration process. Note that such points are only ignored in the registration stage to avoid excess errors. Full

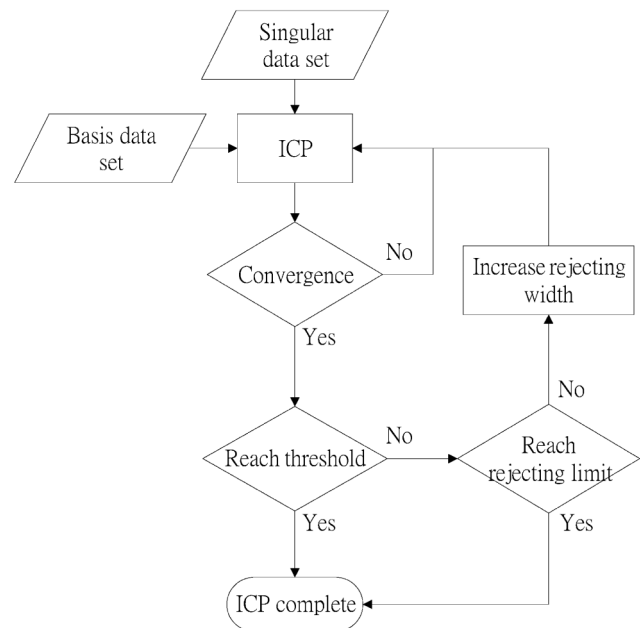


Figure 6. Flowchart of the improved ICP algorithm to reject mismatching points in successive iterations.

datasets, with all points from each scan, are used in the merging process.

The same datasets as those used in Figure 5 are registered using the improved approach. Figure 7 shows how the total differences between the datasets are reduced with the increment of rejection threshold. Just before iteration #20, the total differences began to level out, which means that a good alignment has been found for the current datasets. However, this result is affected by points that cannot be matched and is possibly not the best alignment for the datasets overall. Following the described procedure, we drop the worst matching top 5% of the points and perform registration with the subset of the data. The effect can be seen in the sudden drop of the total difference. The next increase in threshold occurs around iteration #45, then again at about #58. After the third threshold increase, we see that the total difference has fallen below 0.05, which is the acceptable difference. From our experiments, the transformation found at this point will provide a better overall registration for

the datasets. Figure 8(a) shows the result of registering the same datasets as those in Figure 5 using the transformations obtained from the improved ICP algorithm, the

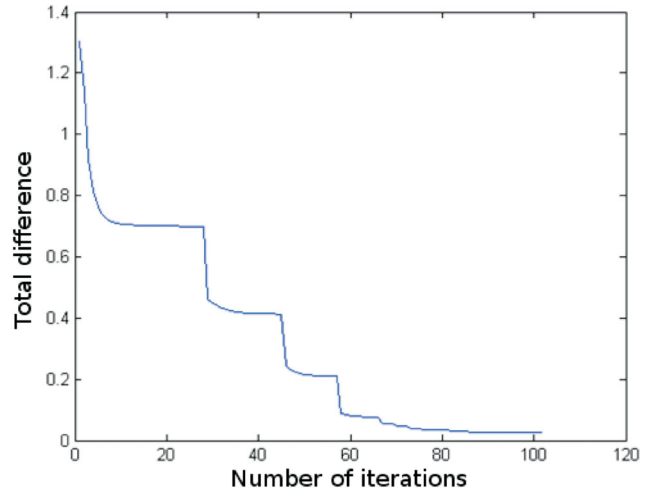


Figure 7. Total difference verses the number of iterations using the improved ICP algorithm to reject mismatching points.

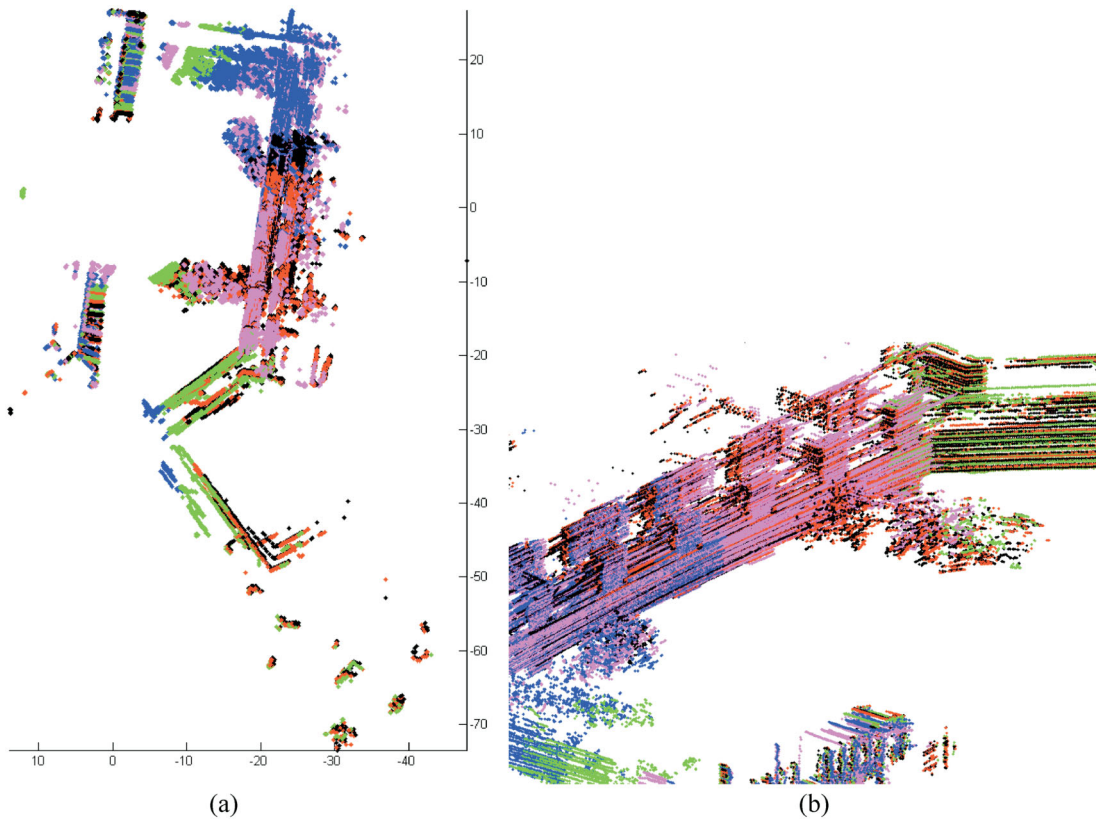


Figure 8. (a) Using improved ICP to register datasets shown in Figure 5 and (b) detailed view of the datasets to show the points are well aligned.

different datasets are shown in different colours. Figure 8(b) is a section of the wall in detail to show that the points are better aligned compared to the results in Figure 5.

3.2 Improving Alignment by Selecting Feature Points

To compare different approaches, we also implemented another version to improve alignment by using feature points that can best represent the dataset in the registration process. For this approach, the dataset is first analyzed to determine points that can be considered as feature points. An octree structure is used to perform this task. Figure 9 shows the points in a dataset being divided into groups that can be represented as nodes in an octree structure. Each rectangular box represents a leaf node in an octree. A box is divided into smaller boxes if there are more than a given number of points in the box. Therefore, at the lower nodes of the octree, we have points that are more densely packed, suggesting that the corresponding region is more significant in 3D space.

Figure 10 shows the improved ICP algorithm using feature points for registration. The process for registration is similar to the algorithm for improving alignment by rejecting mismatching points shown in Figure 6, ex-

cept for the added steps to extract feature points at the beginning. Figure 11 shows the datasets registered by the improved ICP algorithm with feature points. By visual inspection, the datasets are also better registered than using the original ICP algorithm. Other datasets have also been used with similar results.

4. Discussions

Experiments performed on the same datasets have shown that the two proposed approaches perform better than the original ICP algorithm in finding the transformations required to register the datasets. To demonstrate the effectiveness, we compare the error graphs of the different approaches. Figure 12 shows the error graphs for registering datasets obtained at 80 different locations. In the experiment, the average error for original ICP is 0.4 m and from the graph, the average errors for the two proposed approaches are below 0.1 m. In comparison, both proposed approaches show significantly lower errors than the original algorithm. In addition, the improved ICP algorithm using feature points converges to a solution faster than the algorithm to reject mismatching points, since there are fewer points to process. For registration of the datasets obtained at 80 different locations, the ICP

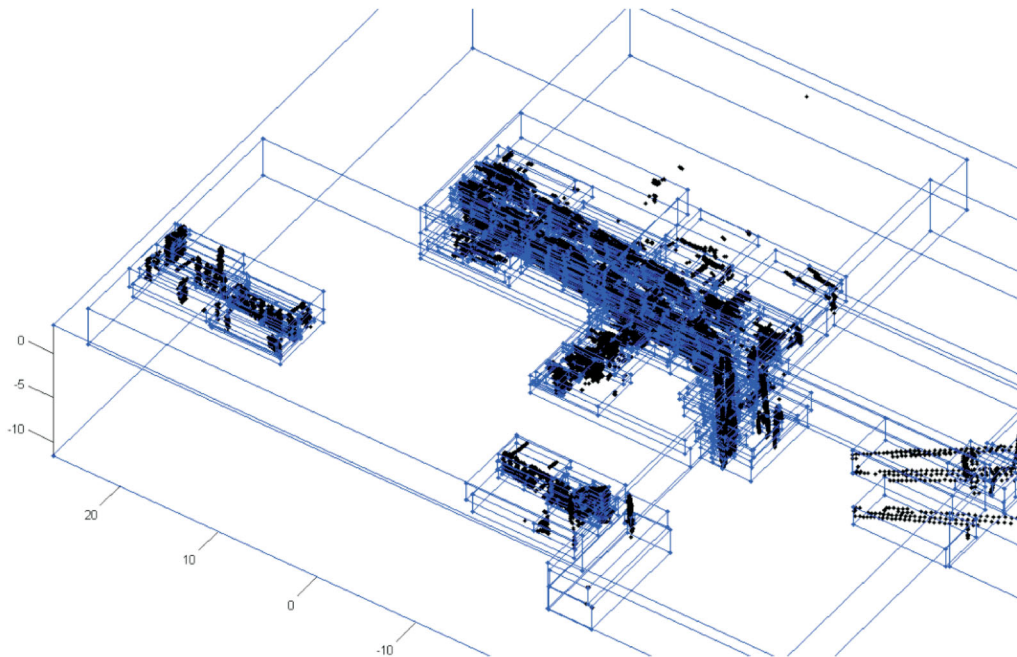


Figure 9. Points in a dataset being divided using an octree structure.

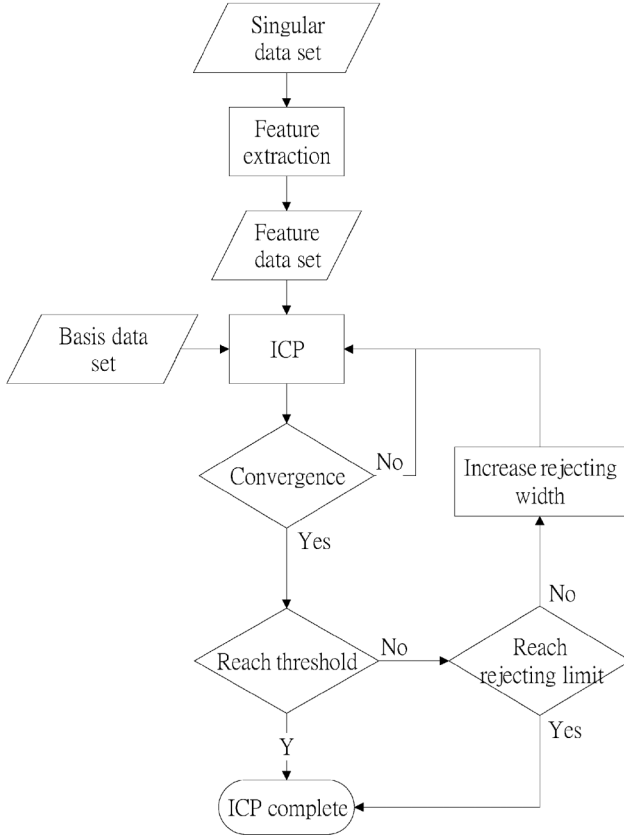


Figure 10. Flowchart of the improved ICP algorithm using feature points for registration.

algorithm to reject mismatching points required 117 iterations to converge to a result below the acceptable threshold, whereas the ICP algorithm using feature points for registration only required 87 iterations to reach the same criterion. The use of octree also allows reduced cost in registration, and the cost can be reduced from $O(n^2)$ to $O(n \log n)$.

5. Conclusions

In this work we have proposed and implemented two methods based on the ICP algorithm to perform automatic registration of large scale range data acquired by a LIDAR device.

The first proposed approach discards points that cannot be matched in the datasets during the registration process to prevent errors from these points from affecting the results. The second approach extracts feature points that are representative of the datasets to perform the registration process and similarly preventing mis-

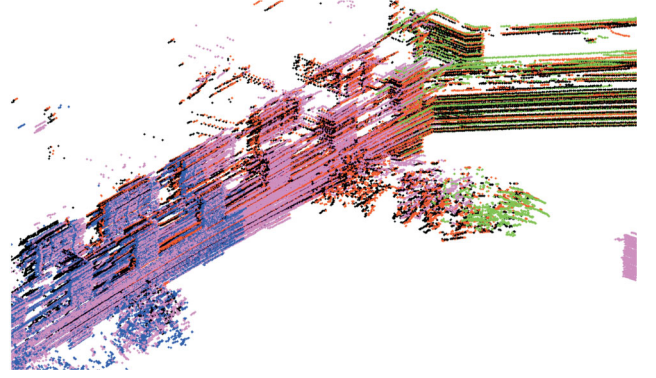


Figure 11. Detailed view of the datasets registered by the improved ICP algorithm with feature points.

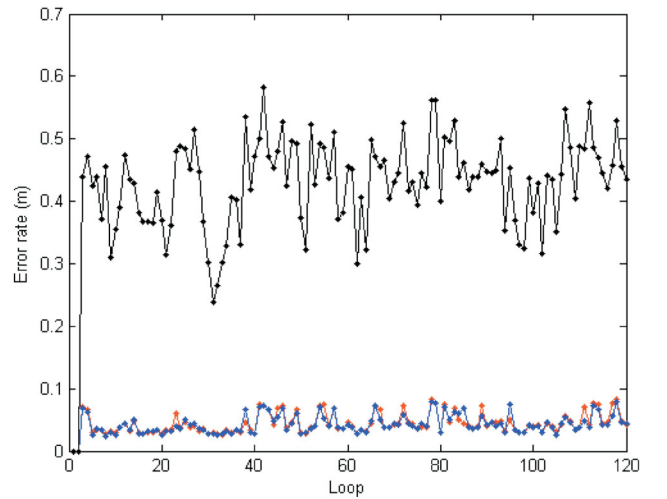


Figure 12. Error graphs for datasets registered using all three algorithms, black is the original ICP, blue is ICP with point rejection and red is ICP with feature points.

matching points from affecting the results. From the experiments, both approaches have been shown to perform better than the original ICP algorithm, which has problems with registrations over a series of datasets due to accumulated errors.

The research described in this paper is one of the first steps required to generate a complete 3D model of the scene. In most of our experiments, the number of datasets processed is well over 100, with each dataset containing more than 20000 points. Therefore, the registration and processing of such large scale data are less than trivial especially when these datasets may contain a lot of noises as well as occluded points which all contribute to the difficulty of the task. Nevertheless, our prelimi-

nary research has shown promising results.

Our final goal is to be able to automatically and efficiently generate a texture mapped 3D model of the scene. We will continue to investigate other possible approaches to improve the registration and fusion process for such huge dataset. In addition, we hope to apply the results of our research in fields such as the digital archiving of archaeological and historical sites, as well as the 3D reconstruction of large scale architecture or geographical landscape.

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