Registration of large scale range data using an improved ICP algorithm approach

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Abstract—**Range data acquired by a LIDAR device can be used to reconstruct a model of the 3D environment. The task of registering and fusing a vast amount of range data is less than trivial. The paper discusses approaches for the registration and merging of the range data to obtain a large scale 3D model of the environment. Experimental results are shown and discussed to demonstrate the performance of the proposed methods.**

Keywords-3D reconstruction; range data; LIDAR; iterative closest point ; ICP

I. INTRODUCTION

Three dimensional reconstructions of objects and scenes have become increasingly significant and popular due to the advancement of technology and demands to provide more detailed information of the environment, or objects. Instead of manually recreating the three dimensional models using graphics based methods, where objects within the scene are constructed using combinations of primitive shapes or user defined coordinates, various 3D reconstruction methods have been developed to acquire 3D data with higher resolution and accuracy. Such 3D reconstruction techniques may utilize calibrated image capturing, or range sensing devices to obtained distance measures of objects within the scene. Compared to manual generation of 3D models, 3D reconstruction techniques can obtain 3D information more quickly and efficiently, and are more versatile in their applications.

One approach to reconstruct a model of the 3D environment is via the use of a LIDAR (Light Detection And Ranging) device [7]. For our work, we have used a device with 64 laser emitters and receivers. The device rotates at 5-15Hz to acquire surrounding range data in real-time, with 0.09 degree angular resolution and 26.8 degree vertical field of view. We have conducted the experiments outdoors, among the buildings in the school. An example of the panoramic view of the scene is shown in Fig. 1, where the device was placed at various locations in the corridors to obtain the range data of the building from different perspectives. Each location provides a 360 degree scan of the surroundings, which needs to be aligned and merged with scans from neighbouring locations to form a complete 3D scan of the building.

Figure 1 One view of the scene to be reconstructed.

Large scale 3D reconstructions of building, or of scenes are often time consuming and results in a large amount of data. Therefore, such reconstructions are unlikely to be performed in real-time. Nevertheless, in conjunction with the device that we are using, which is able to acquire range image of the scene very quickly, we hope to achieve fusion of the 3D data effectively and create detailed large scale 3D models of the scene.

The paper proposes a method to achieve the registration of the point dataset acquired by the LIDAR. The method works by initially performing a rough alignment the dataset using iterative closest point algorithm, then setting criteria to refine the registration and obtain optimal overlapping positions of neighbouring datasets. Additional processing of the point datasets is also performed to remove redundant or erroneous points such that only reliable points are fused to produce the final 3D model of the scene. Experimental results have been provided to demonstrate the effectiveness of the approach in providing more accurate registration of the datasets.

II. ITERATIVE CLOSEST POINT

The iterative closest point (ICP) algorithm is first proposed in 1992 by Besl and Mckay [1]. It is a mainstream method used to register sets of rigid 3D data points. The main idea of the method is to minimize the distances between points in datasets that are to be aligned.

The ICP algorithm starts with two given sets of 3D points, in our case, two sets of 3D data points obtained by the LIDAR device at two different positions within the same scene, represented by $\boldsymbol{X}=\{x_i\}$ and $\boldsymbol{Y}=\{y_i\}$, where x_i and y_i are 3D points represented in Cartesian coordinates. Using the ICP algorithm, we can obtain a transformation matrix, such that a point x_i can be matched to a closest point y_i in the other dataset. The equation below is minimized to obtain the transformation matrix.

$$f(R,p)=\sum_{i=1}^{n}\left\|Rx_i+p-y_i\right\|^2 . \qquad (1)$$

In (1), R is the rotation and p is the translation required to align dataset $\boldsymbol{X}$ to $\boldsymbol{Y}$. An average error is given by dividing (1) by the number of points in the dataset. The point dataset has been preprocessed such that each dataset has the same number of points, n. 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 $\boldsymbol{X}$ and $\boldsymbol{Y}$.

III. PREPROCESSING OF DATA

The LIDAR device is placed at the center of the scene to be reconstructed and acquires raw range data of the scene at frequencies of up to 15Hz. The raw 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. Repeated scans at the same position are discarded. Furthermore, data points close to the limits of the device's scanning range need to be removed since they are more likely to be unreliable. Each of the processed datasets contains a 360 degree scan of the scene at a particular position as shown in Fig. 2. Each scan of the scene is input into the ICP alignment loop to find the optimal parameters for alignment. Finally, the datasets are registered and fused to form the complete 3D scan

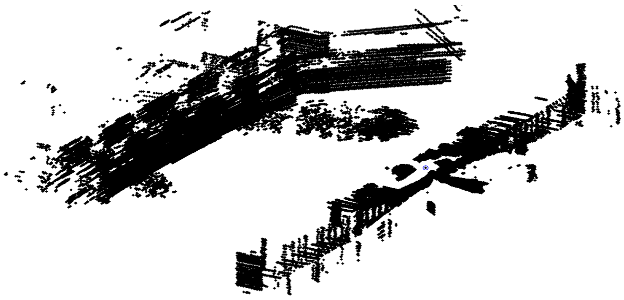

Figure 2 An example of a single 360° scan of the scene.

The ICP alignment loop is responsible for finding the optimal parameters for registration between neighbouring dataset. Details of the steps within the loop are illustrated in Fig. 3.

The first input dataset is used as the basis for aligning consecutive datasets; the next dataset is pre-processed before the alignment process. The following describes the pre-processing operations performed on the datasets before they are being used for alignment.

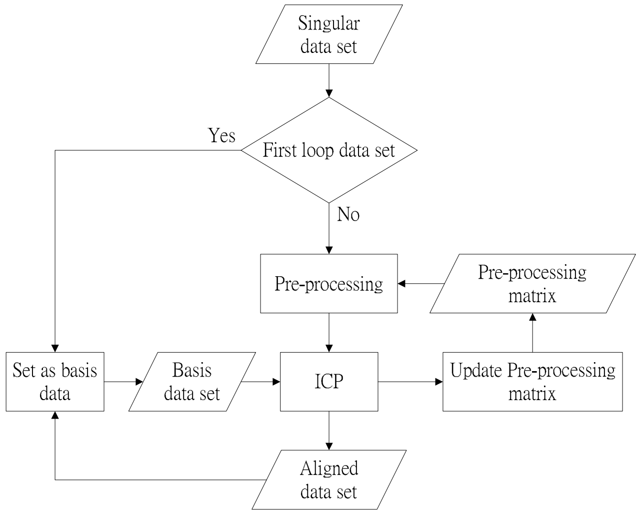

Figure 3 Flowchart of the ICP alignment loop.

A. *Estimation of error*

In using the ICP algorithm for alignment, a tolerance of error must be provided as the criterion for terminating the iterations. Our approach estimates the tolerable error by averaging the errors in aligning 100 scans at the *same* position. The average error thus obtained can be considered as the minimal error threshold due to physical limitations and is used to set the termination error threshold for the ICP algorithm.

B. *Removal of boundary points*

The shortest effective scanning distance for the LIDAR device is 0.9m, points that are detected closer than 0.9m from the device are likely to be erroneous or due to interferences. The longest effective scanning distance for the device is 120m, which is also variable depending on the reflective properties of the objects within the scene. In addition, points that are further away are likely to be more spread out and further away from each other and with lower intensities. Therefore, we also trim off points that are further than 100m away to reduce alignment errors. The red points in Fig. 4 are trimmed off from the original data before being processed further.

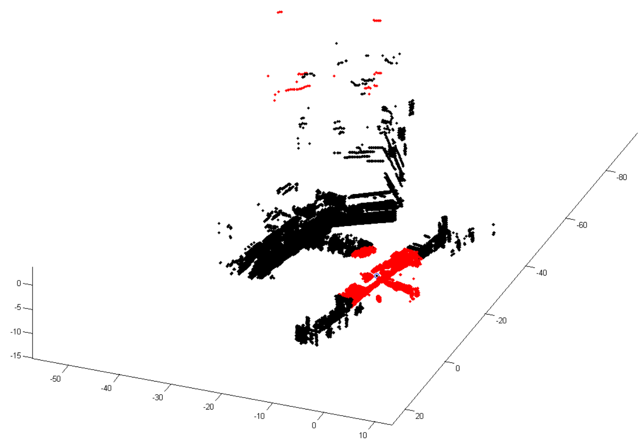

Figure 4 Points to be removed from a 360° scan of the scene.

C. *Application of a transformation matrix*

The 3D reconstructions to be performed in this work are of scenes and buildings which are in the order of hundreds of meters, therefore, the first dataset and the last dataset maybe a long way apart. As each acquired dataset is centered at the location of the device, a dataset needs to be transformed to a location consistent with the previous dataset before being aligned to the previous datasets. A transformation matrix formed by concatenating transformations that have been applied to previous datasets is applied onto the current dataset before it is input into the ICP algorithm for alignment.

Suppose the transformation acquired to align 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},

$$X'_{i+1} = T_1 T_2 ... T_i X_{i+1} \quad . \tag{2}$$

The transformation is to facilitate the alignment process and avoid excessive or erroneous matches at unlikely locations.

IV. ALIGNMENT OF DATA

In our work, we initially use the original ICP algorithm for alignment where the pre-processed datasets are input into the algorithm to find the optimal transformations between each successive datasets. However, due to problems such as occlusion and the fact that the data points are not recorded on a regular, grid-like geometry, the ICP algorithm often fails to provide the most suitable transformation between the datasets. While the ICP algorithm may return the transformation that provides the lowest errors between successive datasets, the transformation may not the correct transformation between the datasets. In addition, as the number of datasets increase, errors are accumulated and propagated onto successive datasets, degrading the result of the registered data. An example showing the problem is given in Fig. 5.

In Fig. 5, the different colours denote different datasets. As the datasets are aligned, the errors between successive datasets become larger and the datasets become further apart instead of perfectly overlapping each other. One cause of the problem is due to the different visibilities of the scene in different datasets. If some points are only present in one dataset, then these points will contribute errors to the ICP calculation, affecting the overall result.

To overcome the problem of accumulated errors, we adopt a strategy known as worst rejection, which excludes points with bad matching properties during the alignment process to avoid unnecessary errors [2]. The following criteria are used for excluding points in a dataset:

- Points among given percentage of worst matching points
- Points with errors larger than a certain threshold
- Points which are within a possible erroneous range [3]
- Isolated points [4]

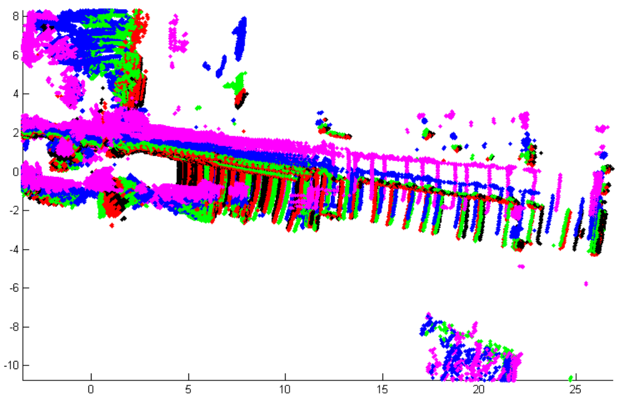

Figure 5 Accumulated errors between aligned datasets

By experimenting with various approaches, we have found that the first condition for excluding points is more suitable and flexible in our application. Therefore, to improve the alignment process, a percentage of points which cannot be matched properly to its neighbouring datasets are excluded from the ICP calculation. Note that the points are only excluded from the calculation process to avoid unnecessary errors, and are still included in all other processing, such as successive alignments and the final merging of the datasets.

The percentage of rejection used in [5] is 10%, but in practice, hardwired threshold value is not flexible enough for successful alignment. As mentioned in [6], a single set threshold may be useful when a suitable threshold cannot be pre-determined. In our experiments, we have experimented with rejection rates from 1% to 40%. It has been found from our experiments that the ICP converges faster with higher rejection rate, but also gives less satisfactory results due to over rejection of points. Hence we implemented a dynamic approach to adjust the rejection rate in the experiment. The rejection rate is initially at 0%, which is essentially the same as a normal ICP alignment procedure. However, when the algorithm has converged to a certain threshold, the rejection rate is raised by 5% to see if a better alignment can be found. The process is repeated until a threshold for rejection rate is reached, at which point, the best alignment encountered so far will be selected. The process is shown in Fig. 6.

The same datasets as those used in Fig. 5 are aligned again using the worst rejection approach. The error rates during the alignment process of two previously misaligned datasets are shown Fig. 7(a). It can be seen that the errors were quite large at the beginning and almost stopped decreasing at around 20 iterations. The reason was that the two datasets contain non matching points which contribute to the overall error.

By applying a 5% rejection rate to exclude the worst matching point, the alignment process started to converge again and the error dropped off quite sharply at around iterations 27-28. Similar behaviours can be observed in later iterations, until the error cannot be reduced any further by the exclusion of points. The resultant aligned datasets are shown in Fig. 7(b). It can be seen that the datasets aligned by excluding non matching points are more consistent than the datasets aligned in Fig. 5.

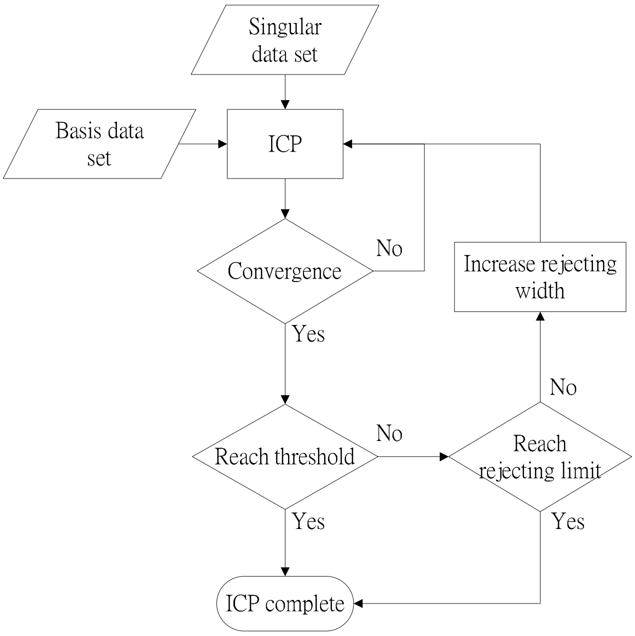

Figure 6 Flowchart for rejection of points

The errors from using the original ICP algorithm and using the worst rejection method for alignment are shown in Fig. 8. It can be seen from the figure that the proposed approach has reduced the alignment errors significantly between the datasets.

V. Conclusion

In this work we have proposed and implemented a method for the automatic alignment and fusion of large scale range data acquired by a LIDAR device. The number of datasets processed is well over 100, with each dataset containing more than 20000 points. The alignment and merging 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.

We have shown that the proposed approach is able to successfully register and fuse the datasets into a 3D model of the scene with relatively low error rate.

Our final goal is to be able to automatically and efficiently generate a texture mapped 3D model of the scene from the range data. Therefore, 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.

Acknowledgment

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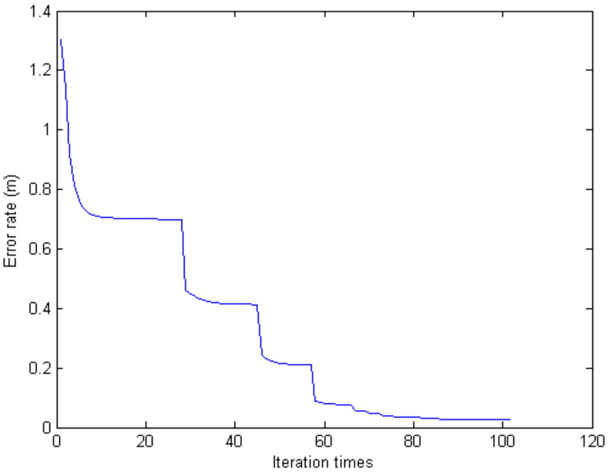
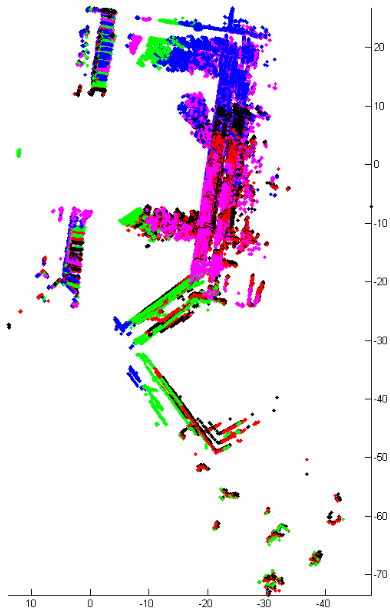


(a)



(b)

Figure 7 (a) Error rate during the alignment iterations with rejected points and (b) the resultant aligned datasets using the described approach.

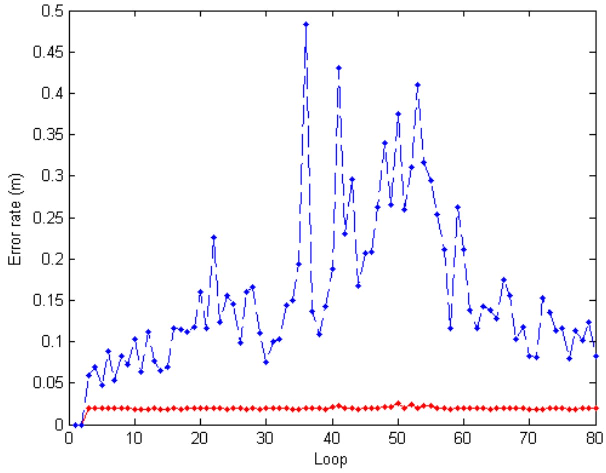


Figure 8 Error rate in alignment of the building corridor over 80 different positions, the average error rate is less than 0.02m using the worst rejection approach (red), in comparison with original ICP algorithm (blue).