An Improved ICP with Heuristic Initial Pose for Point Cloud Alignment

Chien-Chou Lin, Chia-Chen Lin, Chuan-Yu Chang

Department of Computer Science and Information Engineering, National Yunlin University of Science and Technology, Taiwan
linchien@yuntech.edu.tw, peter810916@yahoo.com.tw, chuanyu@yuntech.edu.tw

Abstract

This paper proposes a speed-up approach to find an initial transformation for ICP (Iterative Closest Point) algorithm to improve its performance significantly. The proposed method uses 2D features of bearing angle images to find the corresponding point pairs which speeds up the registration significantly. The proposed method consists of five steps: (1) transforming 3D scans into 2D Bearing Angle Images, (2) extracting features from the 2D images by SURF (Speeded-up robust features), (3) finding the corresponding 3D point pairs respective to the 2D corresponding pixel pairs by the reversed mapping function of bearing image, (4) calculating translation matrices of the corresponding points and (5) finding the optimal transformation between two point clouds by SVD and adopting the optimal transformation as the initial pose of ICP. In simulation results, the proposed algorithm not only greatly decreases the RMSE (Root Mean Square Error) of initial poses but reduces 75% of the iteration times of ICP to a stable state. Furthermore, taking 2D features on bearing angle images as the initial pose of ICP also increases the robustness for larger view angle diversity up to 48 degrees.

Keywords: Point cloud, Alignment, 3D registration, Bearing angle image, ICP (Iterative closest point algorithm), SURF (Speeded-up robust features)

1 Introduction

The 3D registration is aligning partial overlapping several point clouds with variant viewpoints into a common coordinate system. The major task of registration is to find the optimal rotation and translation between the point clouds. By aligning several point clouds into a common coordinate system, the 3D shape of a given object can be reconstructed [1-7]. In most 3D registration procedures, the first step is finding the corresponding points, curves, planes of 3D scenes or other features between the reference and the source. Then, using those corresponding features derives an optimal transformation matrix which can transform the source point cloud to the reference coordinate with minimal error. In [4], Lin et al. proposed an efficient registration method based on features of bearing angle images and its advantage is robust to a larger difference of viewing angle. However, without iterative computing, its alignment error is larger than ICP. In [8], Iterative Closest Point (ICP) algorithm, the most often cited method for aligning two point clouds, was proposed. ICP is based on an iterative process where it first computes the closest point pairs between the point clouds, and then estimates the performed rotation and translation by using a mean squared error cost function. This process is repeated with this new estimate until the transformation is negligible. The details will be reviewed in next section.

Since the ICP finds the closest correspondent of large point set iteratively, the computation cost is huge. The execution time of ICP heavily depends on the choice of the corresponding point-pairs and the distance function. Recently, many variations of ICP have been proposed [9-15]. Those variants can be classified five modified algorithms: (1) subsampling of the available points in one or both meshes. (2) new matching schemes. (3) new weighting function for the corresponding pairs. (4) new rejecting scheme for miss aligned pairs. (5) varying error metric and minimizing approaches. In [9], the reliability of a measure of the shape complexity was used to improve the registration and also used to measure the error of rotation angle. In [10], a modified ICP which takes Euclidean distance and angular distance into account in the cost function of finding the closest correspondent was proposed for 2D scans. The outliers with large angular distance error can discarded efficiently.

Recently, multi-stage ICP algorithms are proposed to avoid an unsuitable initial estimate or local minima. In general, the ICP calculates the distance between two paired points and optimizes the distance by gradient descent. Thus, its performance closely depends on a good initial estimate [15]. In order to efficiently find a

*Corresponding Author: Chien-Chou Lin; E-mail: linchien@yuntech.edu.tw
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good initial estimate between two partially overlapping point clouds of an object, an initial transformation matrix is computed by matching 2D features in this paper. Additionally, we also use all SURF features of two senses as subsampling points to align two point clouds with ICP.

The contribution of this paper is proposing a new approach finding a heuristic initial pose for ICP by using 2D features to speed up the registration significantly. The proposed method, name HI-ICP (Heuristic Initial ICP) initially transforms the point clouds into 2D bearing angle images and then uses the 2D image feature matching method, SURF, to find matching point pairs of two images. Since the transformation from a 3D point cloud to a 2D bearing angle image is a one-to-one mapping, the corresponding 3D point pairs can be obtained easily. Therefore, the initial transformation matrix derived from these corresponding 3D point pairs can be used for further ICP computing. The rest of this paper is organized as follows. The procedure of ICP is reviewed in Section 2. The proposed HI-ICP is given in Section 3. Experimental results and analysis are presented in Section 4. Conclusions are given in Section 5.

2 Review of Iterative Closest Point Algorithm

ICP algorithm, proposed by Besl and Mckay [8], is widely used in registration of 2D or 3D points. The algorithm consists of several steps: finding the closest point in the data shape for each point in the model shape, then estimating the rotation and translation by a mean squared error cost function and transforming the data shape with respect to the obtained rotation and translation. Finally, the best result on alignment will be obtained by iterating the above process until the transformation is negligible. In this paper, the approach of aligning points to points is adopted. Eight steps of ICP algorithm are described as below:

Step 1. Assume there are two point sets, A with m points from the data shape and B with n points from the model shape. Assuming that $A(x_j, y_j, z_j)$ is a point in A and $B(x_k, y_k, z_k)$ is a point in B, the Euclidean distance between the two points is $d = \sqrt{(x_j - x_k)^2 + (y_j - y_k)^2 + (z_j - z_k)^2}$. And the distance between a point $A(x_i, y_i, z_i)$ and a point set B is $d^i_{\min} = \min_{1 \le k \le n} \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2}$. The closest point of $A(x_i, y_i, z_i)$, C_i, is also found.

Step 2. Calculate MSE (Mean Square Error) of the closest point set $C = \{C_i | 1 \le i \le m\}$:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(d^i{}_{\min})^2 \quad \textbf{(1)}$$

where m is the number of point set A.

Step 3. Use SVD (singular value decomposition) to decompose CCM (Cross Covariance Matrix). CCM is a 3×3 matrix. Assume $C = \{C_i | 1 \le i \le m\}$ is the closest point set of A, so the number of set C is equal to set A. CCM is defined as follows:

$$CCM = \frac{1}{m}\sum_{i=1}^{m}\left(\begin{bmatrix} x_i^A - x_C^A \\ y_i^A - y_C^A \\ z_i^A - z_C^A \end{bmatrix} \cdot \begin{bmatrix} x_i^C - x_C^C \\ y_i^C - y_C^C \\ z_i^C - z_C^C \end{bmatrix}^T\right) \quad \textbf{(2)}$$

where $\begin{bmatrix} x_C^A & y_C^A & z_C^A \end{bmatrix}^T$ is the center point of A. P, a 3×3 matrix representing the difference of CCM and the transpose of CCM, can be written as

$$P = CCM - CCM^T \quad \textbf{(3)}$$

Step 4. Draw out a row vector $r = [P_{23} \quad P_{31} \quad P_{12}]$ which forms a Quaternion Matrix Q with CCM. The Quaternion Matrix Q is

$$Q = \begin{bmatrix} trace(CCM) & r \\ r^T & (CCM + CCM^T) - trace(CCM) * I \end{bmatrix} \quad \textbf{(4)}$$

where I is an identity matrix.

Step 5. Calculate the eigenvalue and eigenvector of Q. Assume $\vec{q} = \begin{bmatrix} q_1 & q_2 & q_3 & q_4 \end{bmatrix}$ is the eigenvector of Q, R_q is a rotation matrix in a 3D space and can be written as

$$R_q = \begin{bmatrix} q_1^2 + q_2^2 - q_3^2 - q_4^2 & 2(q_2q_3 - q_1q_4) & 2(q_2q_4 - q_1q_3) \\ 2(q_2q_3 + q_1q_4) & q_1^2 + q_3^2 - q_2^2 - q_4^2 & 2(q_3q_4 - q_1q_2) \\ 2(q_2q_4 - q_1q_3) & 2(q_3q_4 + q_1q_2) & q_1^2 + q_4^2 - q_2^2 - q_3^2 \end{bmatrix} \quad \textbf{(5)}$$

Thus, the translation vector T is defined by

$$T = \begin{bmatrix} x_C^C \\ y_C^C \\ z_C^C \end{bmatrix} - R_q \begin{bmatrix} x_C^A \\ y_C^A \\ z_C^A \end{bmatrix} \quad \textbf{(6)}$$

Step 6. After improved by ICP, A_i' is the improved point set, so $A_i' = R_q A_i + T$

Step 7. MSE (Mean Square Error) is necessary to be recalculated. The MSE is calculated by

$$MSE_{improved} = \frac{1}{m}\sum_{i=1}^{m} {}^{i}_{d\min}{}' \quad \textbf{(7)}$$

Step 8. If $\dfrac{|MSE - MSE_{improved}|}{MSE} < V_{stop}$, ICP stops. Otherwise, repeat the steps from 1 to 7. The V_{stop} is a threshold.

3 Heuristic Initial for ICP

Over the past two decades, ICP has been a very important method widely used to reconstruct 2D shapes or 3D surfaces from different scans. In general, since the ICP uses a MSE distance minimization technique to estimate the best transformation iteratively, it guarantees to converge to a local minimum [8]. However, a convergence to a global minimum depends on a good initial guess [14]. The proposed HI-ICP (Heuristic Initial ICP) takes the best matched pairs of 2D features as initial pose of ICP algorithm for 3D registration. The proposed method based on [4] and [8] consists of five steps: (1) transforming two 3D scans into 2D Bearing Angle Images [1-2, 4, 16] which is a gray level image that presents the angle between a point and its neighbor point and more features can be extracted from the BA image, (2) extracting and matching features from two images by SURF (Speeded-up robust features) [17-18], (3) finding those corresponding 3D point pairs respective to the selected 2D corresponding pixel pairs with a one-to-one mapping between 3D points and BA pixels, (4) finding the best rotation and translation between two corresponding point pairs by SVD algorithm and adopting the best transformation as the initial pose of ICP. (5) using ICP to align two point clouds with the initial pose. The proposed algorithm is shown in Figure 1.

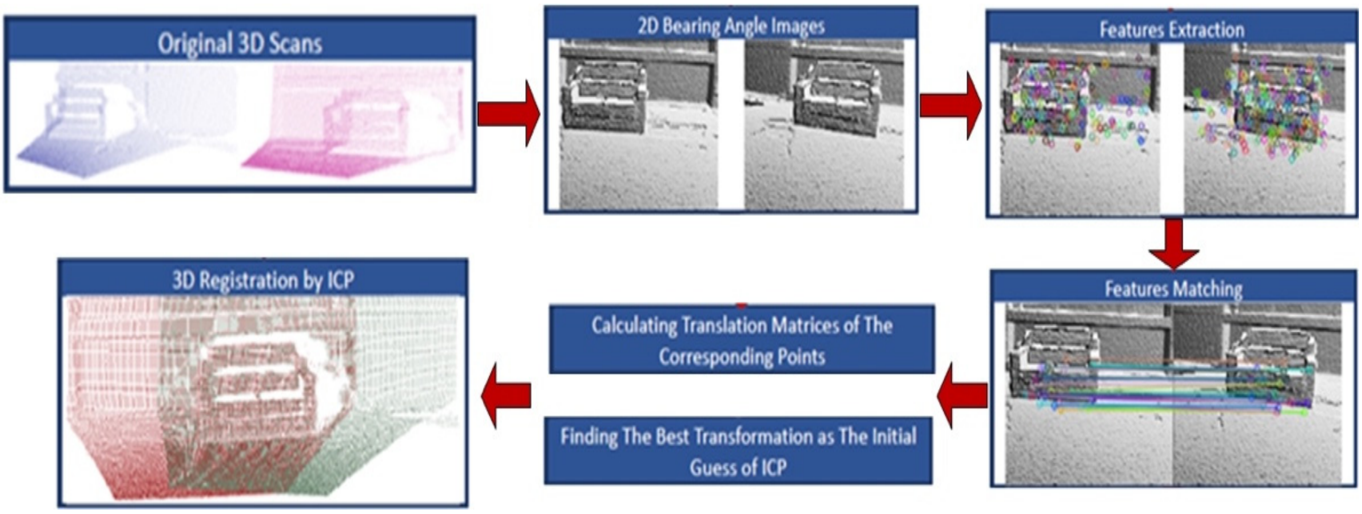


Figure 1. The procedure of HI-ICP for 3D Registration

3.1 Bearing Angle Image

Most approaches in finding corresponding points between two point clouds efficiently, use the features of the 2D images which are projections of 3D surfaces with respect to a viewpoint, e.g., the depth image. However, because the gray value of a depth image is related to the distance of the surfaces, the relation between a point and its neighbor points is not represented in a depth image. In [16], a bearing angle image (BA image) was proposed for calibrating extrinsic parameters between 3D LIDAR and Camera. A BA image is a gray level image that is composed from the angle between a point and its neighbor point and more features can be extracted from the BA image. In this paper, the BA image is used for finding the corresponding points between two point clouds.

The gray level of a pixel of its BA image is defined as the angle between the laser beam and the vector from the point to a consecutive point. This angle is calculated for each point of the shape along the four defined directions which are the horizontal, vertical, or diagonal directions. Considering the laser source, O, and two scan points, $P_{i,j}$ and $P_{i,j+1}$ colored in red and green respectively as shown in Figure 2, $P_{i,j}$ is the j-th scanned point of the i-th scanning layer and $P_{i,j+1}$ is the $(j+1)$-th scanned point of the i-th scanning layer. The bearing angle of $P_{i,j}$ is defined as

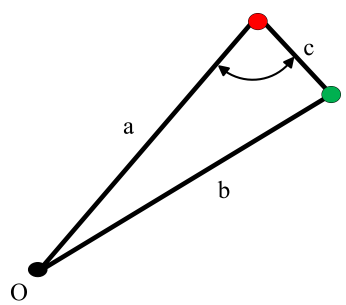
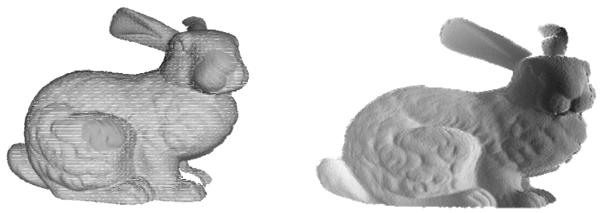


Figure 2. The gray level of a pixel of a BA image is defined as the angle between the laser beam and the vector from the point to a consecutive point

$$\gamma = \cos^{-1}\left(\frac{a^2+c^2-b^2}{2ac}\right) \quad \textbf{(8)}$$

where a and b are the measured range values of $P_{i,j}$ and $P_{i,j+1}$ respectively. And, c is the distance between two points. The gray level of each γ can be obtained by

$\frac{\gamma}{\pi} \times 255$. Figure 3(a) is an example of point cloud and Figure 3(b) is its bearing angle image transformed by Equ. (8).

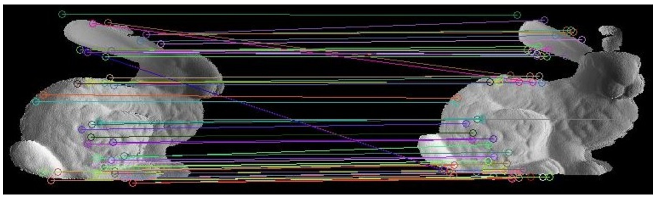


(a) A raw point cloud of Stanford bunny (b) A bearing angle image of Figure 3(a)

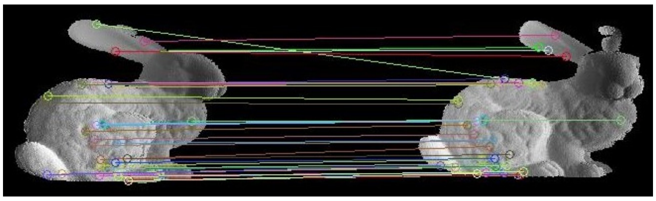
Figure 3. An example of the BA image

3.2 Matching BA Images by SURF

The SURF algorithm [17-18] is adopted to match the two BA images obtained by the previous step. Basically, SURF algorithm contains a feature point extraction stage and a feature point description stage. In the feature extraction, SURF first uses an approximation of Gaussian smoothing operator, box filter, with the integral image. In the feature point description stage, a Haar wavelet is used to calculate directions and strengths of feature points to get a feature descriptor. The feature is represented by 64-dimensional eigenvectors. The Euclidean distances between any two feature vectors are calculated comparing the feature description of two BA images. The corresponding points with the minimum distance are considered as a corresponding point pair. In addition, a good match is determined by the ratio between the minimum distance and the second minimum distance. If the ratio is greater than a threshold, the matching pair is a good corresponding pair of images. After the matching step, several corresponding points are found. Figure 4(a) shows the match result of two bearing angle images by SURF. Some corresponding pixel pairs are not on the objects. When a range image is transformed to a BA image, the contour of the statue is also converted into significant edges which are good features in a 2D image. In SURF based matching, these features will make “good” matched keypoints. However, most of these “good” matched keypoints are misaligned 3D point pairs because one of a pair may disappear after rotating for a few angles. Therefore, those pairs are removed and the new result is shown in Figure 4(b). The reserved matching pixel pairs will be used to find the corresponding point pairs of two point clouds next.



(a) The match result of two bearing angle images of Stanford bunny by SURF. Some corresponding pixel pairs are not on the objects



(b) The result after removed those pairs

Figure 4. Good matches of two bearing angle images of Stanford bunny

3.3 Obtaining Initial Rotation and Translation

In this previous section, the corresponding pixel pairs of the two BA images can be obtained by the SURF. Since S_{ij}, a pixel of a BA image, is obtained from the 3D point of the *j*-th scanned point of the *i*-th layer, the original 3D point of S_{ij} is P_{ij}. The corresponding point pairs can be obtained easily utilizing this method.

Although most of the corresponding pairs obtained by the SURF-based matching method are correct, there are still a few mismatched pairs. If all corresponding pairs are used to derive the initial rotation and translation by SVD approach, the outliers will cause a fake optimal initial position. Therefore, the mismatched pairs have to be discarded in advance to improve the accuracy of the initial pose. The proposed method eliminates mismatched pairs before transforming back to 3D points. In SURF based matching, the feature vector distances between a keypoint of a BA image and every feature point of another BA image are computed. Keypoints between two images are matched by identifying their nearest neighbors depended on the feature vector distances. However, in some cases, the second closest-match may be very near to the first. In that case, ratio of closest-distance to second-closest distance is taken to reject the false matches. When the ratio is smaller than a threshold, the keypoint is selected as a matched keypoint. In this paper, this ratio is also used to sort all matched keypoints because not all matched keypoints are used for deriving the initial pose. In order to reduce the outliers, only the top two-thirds of the corresponding pairs are used to find the initial translation and rotation since they can be identified as correct with high confidence.

In this paper, we use the SVD-based method [19] to find the least-squares solution of rotation and translation between two corresponding point clouds, P and Q. First, it is assumed that the translation is the centroid of P to the centroid of Q. Thus, restating the problem without translation, the points of two sets are rewritten as

$$p_{ic} = p_i - \overline{p}; \qquad q_{ic} = q_i - \overline{q} \tag{9}$$

where $\overline{p}$ and $\overline{q}$, the centroids of two sets, are expressed by

$$\overline{p} = \frac{1}{m}\sum p_i; \qquad \overline{q} = \frac{1}{m}\sum q_i \tag{10}$$

The new corresponding point sets are P_c and Q_c. Since the optimal rotation $\hat{R}$ implies the minimal transformation error, the relation can be expressed as

$$\hat{T} = P_c - \hat{R}Q_c = \overline{p} - \hat{R}\overline{q}\ . \tag{11}$$

In order to find the optimal rotation, a 3X3 matrix, H, has to be obtained firstly.

$$H = \sum_{i=1}^{N} p_{ic} q_{ic}^{T} \tag{12}$$

Then, decompose H as SVD form

$$H = U \Lambda V^T \tag{13}$$

And, $\hat{R}$ is obtained by

$$\hat{R} = VU^T \tag{14}$$

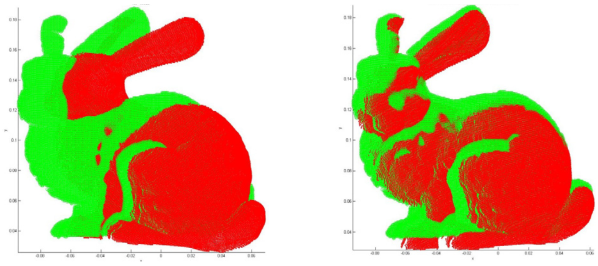
Thus, the optimal transformation is represented as

$$Q = \begin{bmatrix} x' \\ y' \\ z' \\ 1 \end{bmatrix} = T(P) = \begin{bmatrix} & \hat{R} & & \hat{T} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{15}$$

where $\hat{T} = \overline{q} - \overline{p}$ and $\hat{R} = VU^T$. The best corresponding point pair will be taken as the initial pose of ICP Algorithm for 3D Registration. Figure 5(a) is the two original scan of Stanford bunny and Figure 5(b) is the initial pose obtained by the proposed algorithm. It is easy to see that the alignment is almost complete. In Figure 6, the 3D registration result by HI-ICP is shown.

4 Simulation Result

The simulation includes two cases from Stanford 3D scanning repository. The first case is Stanford bunny as shown in Figure 3. The proposed algorithm is used to align two point clouds from viewpoint 0^o and 45^o. The initial poses of two given point clouds are shown in Figure 5(a) and the initial pose of HI-ICP is shown in Figure 5(b). The aligned result is shown in Figure 6. A comparison of RMSE (root mean square error) of every iteration between HI-ICP and ICP is shown in Figure 7. The RMSE of the initial pose of HI-ICP is 0.003229 which is one tenth of the conventional ICP's RMSE. The RMSE of the HI-ICP reaches a stable stage after the third iteration, but the conventional ICP takes eleven iterations. It is obvious that the HI-ICP reaches a stable stage around its best RMSE much earlier than the conventional ICP.



(a) The initial pose of two given point clouds (b) The good initial pose of HI-ICP

Figure 5.

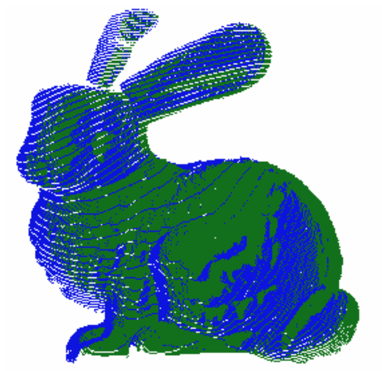


Figure 6. 3D registration result by HI-ICP

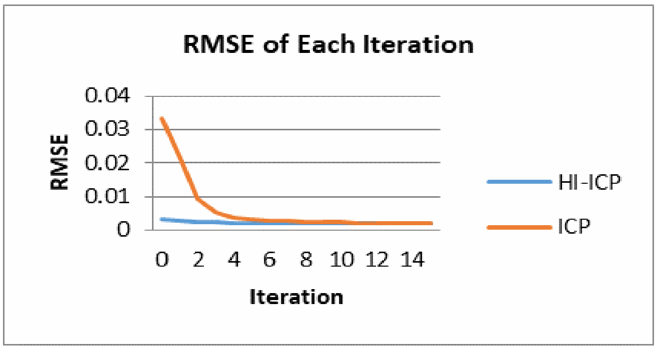
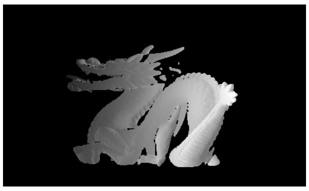


Figure 7. A RMSE comparison between HI-ICP and ICP. (unit: m)

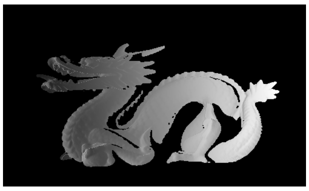
The second case is Dragon of Stanford 3D scanning repository. The test data includes several poses in different orientations. In our simulation, the range images in 0^o, 24^o, 48^o and 336^o are used and their BA images are shown in Figure 8. The proposed algorithm performs well for aligning two point clouds obtained within 48 degrees. In Figure 9, the BA images of viewpoint 0° and 48° are shown in the left-hand side and the right-hand side of Figure 9 respectively. The matched pixel pairs obtained by SURF are also marked in Figure 9. Most of the matched pixel pairs are correct. The aligned result of HI-ICP is shown in Figure 10. A comparison of RMSE of iterations between HI-ICP and ICP is shown in Figure 11(a). It is obvious that the HI-ICP also reaches a stable stage around its best RMSE much earlier than the conventional ICP in this case. Figure 11(b) shows the alignment of two point clouds in different orientations (336° and 24°).

(a)



(b)

(c)



(d)

Figure 8. The bearing angle images of the range images of Dragon in 0°, 24°, 48° and 336°, respectively

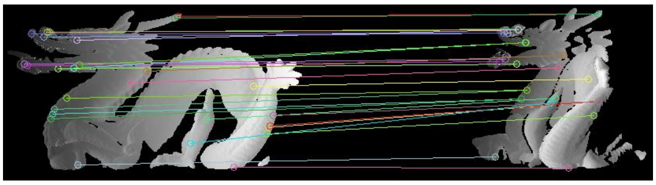


Figure 9. Good matches of two bearing angle images of Dragon

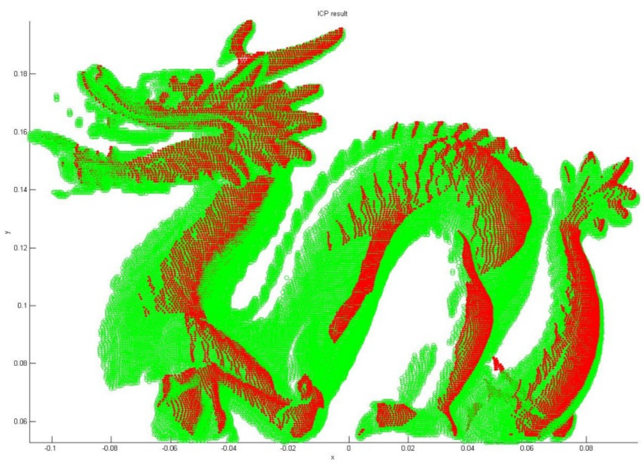
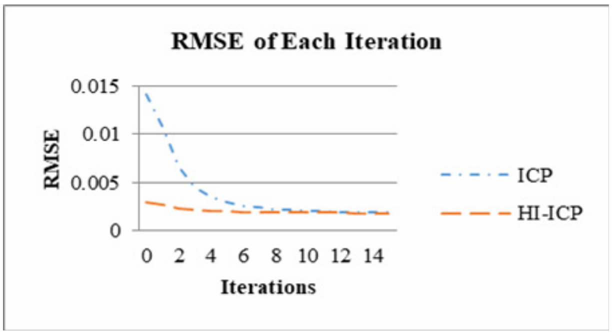
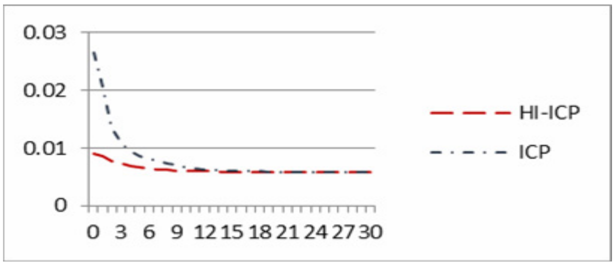


Figure 10. 3D registration result of Dragon by HI-ICP



(a) The alignment of two point clouds in different rotations (0° and 48°)

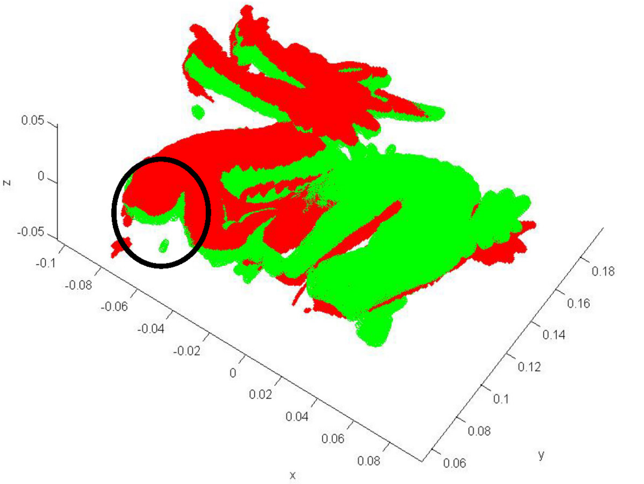


(b) The alignment of two point clouds in different orientations (336° and 24°). (unit: m)

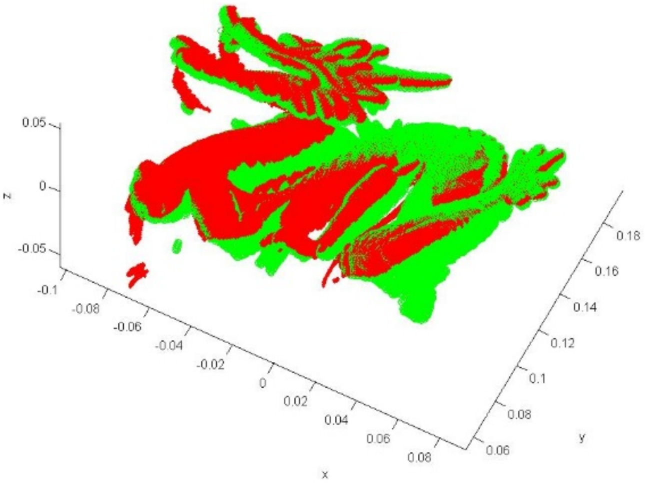
Figure 11. RMSE comparison between HI-ICP and ICP

In this simulation, we also use a SURF feature subsampling approach with ICP. The SURF features of a sense are about 200 points and these two point sets are aligned by ICP. In Figure 12(a), the result which RMSE is converged to 0.0071 after 15 iterations is shown. The displacement marked by a circle in blue is obvious. In Figure 12(b), the result of the same viewpoint of the HI-ICP is shown. Comparing two results, the SURF feature subsampling approach with ICP is worse than HI-ICP because the optimization falls into a local minimum caused by using only 200 points (less 1% of original data) to align two senses while ICP is a brute-force search based method which matches all points and gets a better result. However, in some real-time applications, the proposed SURF based subsampling ICP is a good choice because the computation is reduced to less 1%.

In the third case, we use two consecutive point clouds of a car seat scene captured by our LIDAR system and the disparity between the point clouds is 30°. The color image of the sense is shown in Figure 13(a). The aligned result of HI-ICP and Generalized-ICP are shown in Figure 13(b) and Figure 13(c) respectively. It is obvious that Generalized-ICP does not align two point clouds well in this case. Because the error metric and the minimization approach of Generalized-ICP is misled by a lot of corresponding ground points, the ICP is trapped in a local minimum. A good initial pose can prevent the ICP from such a local minimum.

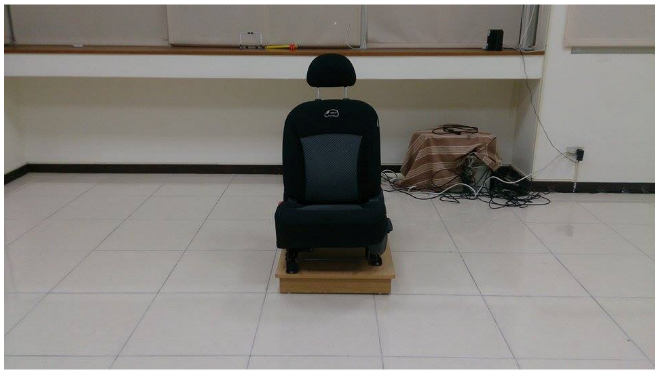


(a) The alignment of two given point clouds with SURF feature subsampling (EMRS=0.0071)

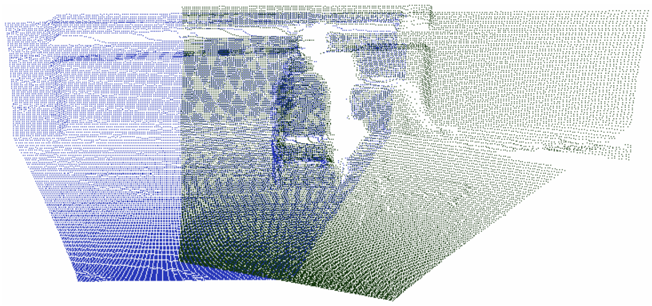


(b) The alignment of HI-ICP (EMRS=0.0052)

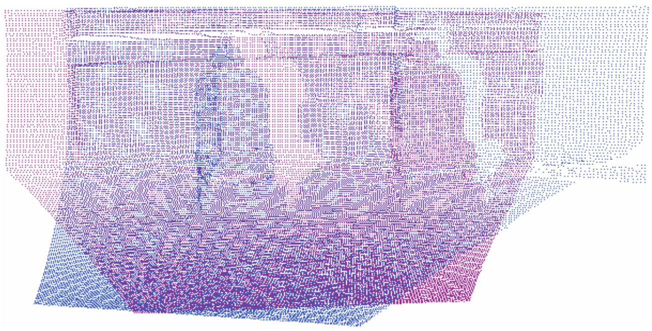
Figure 12.



(a) A scene with a car seat



(b) The result of HI-ICP



(c) The result of Generalized-ICP

Figure 13.

4 Conclusion

This paper proposes a new method using a good initial pose to speed up the ICP which usually requires huge computation and depends on a good initial pose to converge to a global minimum. The proposed method uses 2D features of BA images instead of complex 3D features to find the corresponding point pairs. Since SURF-based matching has high reliability, the derived initial pose gives a good coarse alignment.

The main contribution of this paper is (i) proposing a fast and robust approach in finding corresponding point pairs and (ii) speeding up the ICP significantly. In the simulation, the initial pose of HI-ICP successfully reduces the 90% of RMSE at the outset. Furthermore, the iteration number of HI-ICP to a stable state is also reduced. Since the 2D features of bearing angle images are considered for matching, the proposed algorithm is more robust than conventional ICP in variation of angle. In the experiment, the overlapping section of two point clouds is less than 50%. The ICP fails to align, but the proposed HI-ICP still works well. There are other potential research topics which can be considered for further future discussion. First, the approach based on BA image may be used for 3D object matching. This is because, for 2D image, the SURF can successfully be used for finding sub-image in a big image. The other topic is examining the reduction of mismatched pixel pairs and point pairs. The outlier of pixel pairs and point pairs degrade the performance of the proposed algorithm.

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Biographies

Chien-Chou Lin received his Ph.D. degrees from National Chiao-Tung University, Taiwan, in 2004. From 2010 to 2013, he was an assistant professor, and since 2013 he has been an associate professor at National Yunlin University of Science and Technology, Taiwan. His research interests are robotics, point cloud processing, surface matching, and object recognition.

Chia-Chen Lin received her M.S. degree in computer science and information engineering from National Yunlin University of Science and Technology, Yunlin, Taiwan, in 2016. Since 2018, she has been a research assistant at National Yunlin University of Science and Technology. Her research interests include robotics, path planning, and object recognition.

Chuan-Yu Chang received his Ph.D. degree in electrical engineering from National Cheng Kung University, Tainan, Taiwan, in 2000. From 2007 to 2010, he was an associate professor, and since 2010 he has been a full professor at National Yunlin University of Science and Technology, Taiwan. His research interests include neural networks and their application to medical image processing, wafer defect inspection, digital watermarking, and pattern recognition.