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Color Point Cloud Registration with 4D ICP Algorithm

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Abstract—**This paper presents methodologies to accelerate the registration of 3D point cloud segments by using hue data from the associated imagery. The proposed variant of the Iterative Closest Point (ICP) algorithm combines both normalized point range data and weighted hue value calculated from RGB data of an image registered 3D point cloud. A k-d tree based nearest neighbor search is used to associated common points in {x, y, z, hue} 4D space. The unknown rigid translation and rotation matrix required for registration is iteratively solved using Singular Value Decomposition (SVD) method. A mobile robot mounted scanner was used to generate color point cloud segments over a large area. The 4D ICP registration has been compared with typical 3D ICP and numerical results on the generated map segments shows that the 4D method resolves ambiguity in registration and converges faster than the 3D ICP.**

I. Introduction

The generation of dimensionally accurate 3D maps is of interest to many domains such as surveying, rescue, security, defense and construction. Laser based scanning device have been applied to generate point clouds which portray spatial information about objects and environments [1].These scanners generate high density 3D point clouds using precise high speed rotary mechanisms and sensors. Corresponding optical imagery from a color camera can also be associated with 3D point clouds to produce visually realistic 3D color point clouds. The 3D color point cloud contains both distance and texture information, which provides a richer representation of the scanned environment and allows for easier identification of objects within the scan [2].

Large scale 3d maps can be generated by acquiring 3D scans from multiple locations. The individual scans acquired at different locations have to be combined together as complete large scale map based on vantage point position and orientation information. Algorithms to associated point clouds obtained from two vantage points that are sufficiently close to each other can be divided into Iterative Closest Point (ICP) related techniques, ICP variant related techniques and non-ICP techniques. A Point to point association strategy is used in the Iterative Closest Point (ICP) algorithm. It is the most popular registration algorithm for point cloud map registration [3]. In an ICP algorithm closest points in different point clouds are associated and optimal rigid transformation that minimizes a mean-square error of separation between the associated points of the two data sets [8] is iteratively computed. Upon convergence, ICP algorithm has been proved to terminate at a minimum error[9]. Singular Value Decomposition (SVD) method [10], eigen-system method and dual quaternion techniques are commonly used to determine the minimum average distance between matched points in two point clouds [11]. In recent years SVD based algorithms have been widely used in ICP and 6D SLAM [12, 13, 15] due to their robustness and ease of implementation.

3D color point clouds can be generated by integrating a color camera onto a custom built 3d LIDAR [14]. By applying proper calibration on the hybrid sensor system [13, 16], range measurement and visual information can be integrated together to construct a visually realistic and geometrically accurate representation of the scene. Color mapped 3D data was used to enable registration of individual 3d scans by using weighted red, green, blue data. The corresponding point search can be finished based on both dimensional and color data during the ICP process. The hue (from the Hue-saturation-lightness model) of each point is classified and used as a filter to constrain the closest point search in every ICP iteration [17, 18]. Color data on range image can be used to estimate initial alignment of pair wise scans via Scale Invariant Feature Transform (SIFT), color attributes transferred in YIQ color model are weighted to construct new variant together with range information for ICP fine registration [16]. Depth-interpolated Image Feature (DIFT) algorithm solves corresponding points between 2 imagery and register color point cloud based on extracted correspondences [19]. Probabilistic scan registration traces laser beam to exploit maximum range readings to increase likelihood of alignment [20]. Point cloud surface normal distributions are helpful in coarse registration. Point cloud surface normal vector distribution can be translated in to orientation histogram as Extended Gaussian Image (EGI) [21] and rigid motion between different scans can be solved from the cross covariance function [22]. Rigid motion could also be solve in Fourier domain by computing Discrete Fourier Transform on Rotation Group on SO(3) (SOFT) [23]. Color attribute has been applied as kernel extension in Normal Distributions Transform (NDT) process so that robustness is increased [23]. In most cases, normal based registration methods are applied for point cloud rough alignment, ICP based algorithms are utilized for fine registration.

This paper presents a hue assisted 4D ICP algorithm that makes use of data from color laser ranging system. The key idea is to apply weighted hue value with 3D coordinate data to increase point registration speed and accuracy. Point association takes place in solving ambiguities that can occur with 3D point cloud map alignment. The performance of point association during ICP process can be advanced by hue data.

II. Color Point Cloud Generation

Color point clouds are created by using a video registered 3D LIDAR scanning system. The system makes use of a 2D LIDAR scanner mounted atop a rotary mechanism. The LIDAR is oriented to produce a vertical 2D scan and the mechanism is rotated about the vertical axis. A rotary position sensor is used to measure the angle of the mechanism during each scan and serves as the third dimension of a spherical coordinate system used to produce 3D scans. Calibrated high speed video cameras are mounted onto of the scanner and used to colorize the 3d data in real-time (Fig. 1).

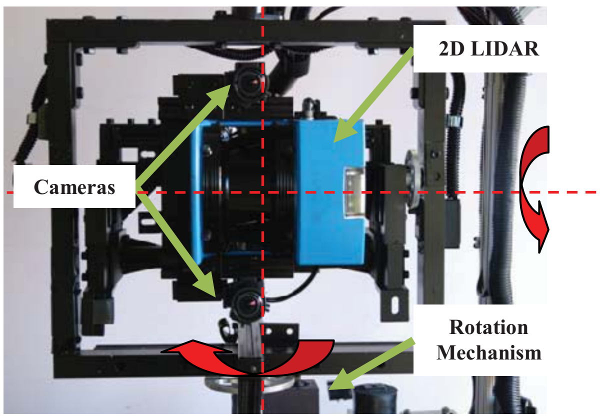


Figure 1. 3D color Lidar scanning system

The scanning mechanism is mounted on top of a mobile electric platform named ROAMS (Remotely Operated and Autonomous Mapping System) to enable the generation of large scale maps (Fig. 2) [13]. The system can be operated wirelessly from large distances and can enable the generation of maps of remote locations. To generate large scale maps ROAMS is driven to various location around the scan area and 3d color scans are taken at each location.

Figure 2. Remotely Operated and Autonomous mapping system (ROAMS)

III. Hue Assisted ICP Algorithm

Hue value can be applied to increase the accuracy of point association. The majority of the time and computation cost during the ICP process is spent on trying to find correct point pairs. Closest spatial distance rule is utilized for typical 3D ICP method. The point cloud distance value in 3D space can be expanded into 4D space by adding weighted hue value as the 4th dimension. By integrating hue value into the closest point search, accuracy of point association can then be improved.

A. Hue Invariance with Vantage Point

Hue value remains consistent for the same point between images taken from two vantage points, while the color values represented in red, green and blue quantities usually differ because of variation in light conditions. In order to effectively apply color to improve the association process, lighting effect should be removed. Raw RGB color data is transformed into representation of separate chroma, lightness and brightness value. Figure 3 shows two camera images take at different angles of a color palette on a Rubik's cube, four colors are used on the same surface. Figure 3 also shows the color pixels with the background and black frame removed. Histograms showing the red, green and blue value in RGB space for all the pixels are shown in figure 4. In the RGB histogram, R, G, and B distributions of the image vary considerably with the vantage point. When the RGB color space is transformed into HSL space and histograms of hue, lightness and saturation are plotted in figure 5, the hue values remain relatively invariant with the position of the camera. Therefore, hue value of the pixel taken from the Hue-Saturation-Lightness (HSL) model is used as the fourth dimension in the color point association process.

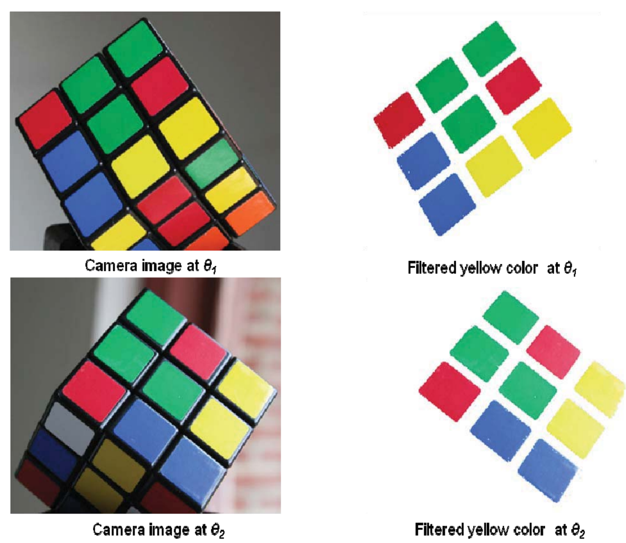


Figure3. Rubik's cube camera images take from 2 different angles

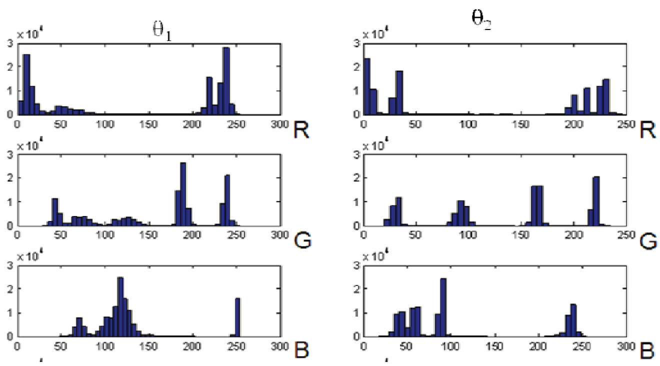


Figure 4. RGB distributions change with camera positions (θ_1, θ_2)

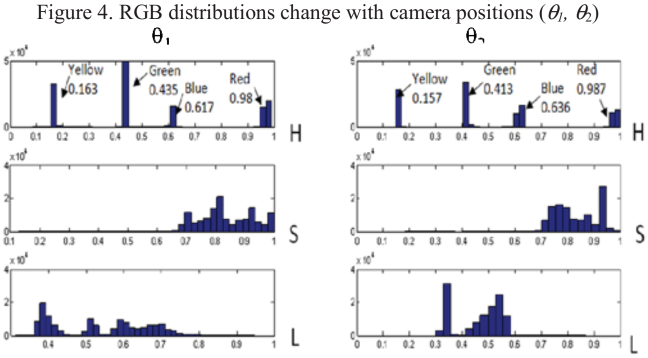


Figure 5 HSL distribution: hue remains invariant

B. Algorithm for Hue-Assisted ICP

Both hue and range value have to be combined together in the 4D ICP variant as $\{x_o, y_o, z_o, h_o\}$ for point association. x_o, y_o, z_o are the original coordinate values with distance units and h_o is the original hue value. Hue values are normalized from 0 to 1 and must be weighted during the closest point search in the four-dimensional space. h_w is the normalized and weighted hue value. In order to normalize the coordinates, the maximum range of the scanner is used and the coordinate space is rescaled to a 0-1 range. The normalized variant for point association is $\{x, y. z, h_w\}$, where $x=x_o/2r_{max}+0.5$, $y=y_o/2r_{max}+0.5$, $z=z_o/2r_{max}+0.5$, r_{max} is the max range of LIDAR.

The weight value for the hue dimension should be properly selected for point association. Since both range and hue value are normalized from 0 to 1. Weight for hue represents its influence in the nearest neighbor search process. Low weight biases the point association towards the range data and a high weight towards the hue values. Small weight values for the hue correspond to the traditional 3D-ICP. Experimental results have shown that a hue weight 10% and 35% of 3D range search distance produced the best results for accurate point association. Error in 4D ICP will be evaluated by calculating the average mean square root distance of the associated point pairs.

The Hue-assisted ICP algorithm entails the following steps:

1. Estimate the initial values for the matrices ***R*** and ***T*** that transform points in the data point cloud into the model point cloud's coordinate system.

2. Construct k-d tree of model point cloud ***M{m₁,m₂,m₃...m_M}***, with weighted hue value as the 4^{th} dimension;

3. ***While*** merging error ε > *preset tolerance*

3.1 Use ***R*** and ***T*** to transfer data point cloud ***D{d₁,d₂…d_N}***: $\overline{D}=R\overline{D}+T$

3.2 Nearest Neighbor Association Step:

For *i*=1 ***to*** Number of points in the data point cloud

Set Number of Associated Points N = 0

Search closest point for point $\boldsymbol{d_i}$ $\{d_{ix}, d_{iy}, d_{iz}, d_{ih}\}$ in model *k*-d tree

If closest point $\boldsymbol{m_j}$ exists within a specified search range, *r*

Associate $\mathbf{d_i}$ and $\mathbf{m_j}$ as $\{\mathbf{d_k}, \mathbf{m_k}\}$;

Increment number of associated points++:

End If

End For

3.3 Distance error Computation: For each associated point pair, calculate normalized mean square root distance ε *as* error,

$$\varepsilon=\frac{1}{N}\sum_{i=1}^{N}\sqrt{(d_{ix}-m_{ix})^2+(d_{iy}-m_{iy})^2+(d_{iz}-m_{iz})^2}$$

3.4 Solve for R and T that minimize ε: Construct orthonormality matrix ***H*** (Eq.7) and solve rigid rotation ***R*** and translation ***T*** (Eq.8 & 9);

End While

4. ***Post-Registration error estimates:*** Compute any post registration errors such as planarity or curvature continuities.

C. k-d Tree Based Point Cloud Association

In 3D ICP algorithm, corresponding points are searched according to the closest distance rule. This may cause incorrect matching during single iteration loop and takes more than 1 iteration to pair correct nearest neighbor points for given data points set. Based on correct hue property, the best neighbor in the model can be found in one iteration. Depending on the correct color information, corresponding point can locked with less iteration.

The ICP computation speed and precision are highly dependent on association process. Use of a k-d tree for closest point search and association or the Nearest Neighbor Search (NNS) problem increases the speed and efficiency of the search. The k-d tree is a spatial partitioning data structure that stores and organizes data in a *k* dimensional space. The k-d tree is a generalized type of binary tree, with every leaf node is a k-dimensional data point that splits the hyperspace into two subspaces. Splitting is done sequentially from the first dimension to the k^{th} dimension.

Nearest neighbor search can be done very efficiently on k-d trees. For a given point with known coordinates in the data point cloud and a search radius, the algorithm recursively moves down the tree and follows the same procedure as insertion. Search stops at a leaf node of the tree and the points in the model tree within the search radius are identified. The nearest point is obtained using distance computation and then is regarded as the point associated with the search point.

In 3D closest point search, the distance between 2 points in 2 neighboring point clouds is:

$$r_{ij}=\sqrt{(m_{ix}-d_{jx})^2+(m_{iy}-d_{jy})^2+(m_{iz}-d_{jz})^2} \qquad (1)$$

In which, $\boldsymbol{d_i}\{d_{ix}, d_{iy}, d_{iz}\}$ and $\boldsymbol{m_j}\{m_{jx}, m_{jy}, m_{jz}\}$ are point spatial coordinates in data and model point cloud map respectively.

In 4D space, the 4th dimension for each point should be weighed hue value d_{hw} and m_{hw}. The spatial value of points should be normalized by 3D search radius r_{ij} in Eq. (1). In order to accomplish closest point search in 4D space, the distance between two normalized points $\boldsymbol{d_i}\{d_{ix},d_{iy},d_{iz},h_{ihw}\}$ and $\boldsymbol{m_j}\{m_{jx},m_{jy},m_{jz},m_{jhw}\}$ should be:

$$r_{ij}' = \sqrt{(m_{ix}-d_{jx})^2+(m_{iy}-d_{jy})^2+(m_{iz}-d_{jz})^2+(m_{ihw}-d_{jhw})^2} \quad (2)$$

$$r_{ij}' = \sqrt{r_{ij}^2+\Delta h_{ijw}{}^2} \quad (3)$$

In the ICP process, search radius effects the computation time and final result. A constant search radius is applied for all iterations. If the search radius is large, too many points will be included as candidates during association. On the other hand, if the search radius is small, the points may not be associated and more iteration will be required. The optimal search radius depends upon the density of point cloud and the initial position estimation. In 4D k-d tree search, the search radius is based on both the coordinate data as well as the weighted hue as shown in Eq. (3). As a rule of thumb, search radius is typically selected to yield about 50 candidate points. If a substantial weight is used in the construction of 4-D space, the k-D search will bias toward hue dimension and the 4D ICP algorithm will behave close to a applying a hue-filter to the system.

Strictly coordinate based association may result in non-unique registration. For example, if the points in the model and the data point clouds belong to a plane, coordinate based ICP results in non-unique association of points. In such cases using the hue value may result in unique registration of the points.

D. Error Minimization

If $m_i = \{m_{ix}, m_{iy}, m_{iz}\}$ represent the coordinates of the i^{th} point in the model point cloud and $d_j = \{d_{jx}, d_{jy}, d_{jz}\}$ are coordinates of the j^{th} point in the associated or paired point set, a distance error is defined as given in Eq. (4).

$$E(R,T) = \frac{1}{N}\sum_{i=1}^{N}\left\| m_i - (Rd_i + T)\right\| \quad (4)$$

Centroids are computed for the associated points in both model and data point clouds as shown in Eq.5. The coordinates are translated to have the origin at the centroid as given in Eq.6. An orthonormal transformation matrix of associated points can be constructed (Eq.7). Rotation $\boldsymbol{R}$ and translation $\boldsymbol{T}$ are decoupled. Using Singular Value Decomposition (SVD), $\boldsymbol{R}$ can be solved from the orthonormality matrix (Eq.8). Translation $\boldsymbol{T}$ is computed by translating the centroids of model and data point sets (Eq.9).

$$\overline{m} = \frac{1}{N}\sum_{i=1}^{N} m_i \quad , \quad \overline{d} = \frac{1}{N}\sum_{i=1}^{N} d_i \quad (5)$$

$\overline{m} = \{\overline{m}_x, \overline{m}_y, \overline{m}_z\}$ and $\overline{d} = \{\overline{d}_x, \overline{d}_y, \overline{d}_z\}$ are the centroids of associated points in model and data point clouds. N is the total number of associated points. The coordinates after transformation are:

$$m_i' = m_i - \overline{m} \quad , \quad d_i' = d_i - \overline{d} \quad (6)$$

$m_i' = \{m_{ix}', m_{iy}', m_{iz}'\}$ and $d_i' = \{d_{ix}', d_{iy}', d_{iz}'\}$ are the i^{th} associated point about the transformed coordinate system. The orthonormality matrix H can be constructed based on $m'\{m_i', i=1\ldots N\}$ and $d'\{d_i', i=1\ldots N\}$.

$$H = \begin{bmatrix} S_{xx} & S_{xy} & S_{xz} \\ S_{yx} & S_{yy} & S_{yz} \\ S_{zx} & S_{zy} & S_{zz} \end{bmatrix}$$

Where

$$S_{yy} = \sum_{i=1}^{N} m'_{iy} d'_{iy} \qquad S_{xx} = \sum_{i=1}^{N} m'_{ix} d'_{ix}$$
$$S_{zz} = \sum_{i=1}^{N} m'_{iz} d'_{iz} \qquad S_{xy} = \sum_{i=1}^{N} m'_{ix} d'_{iy} \quad (7)$$

Singular value decomposition is performed for the $\boldsymbol{H}$ matrix to determine the rotation matrix, **R,** that minimizes the error as:

$$H = U\Lambda V^T \quad (8)$$

Where optimal rotation $R = VU^T$. The translation $\boldsymbol{T}$ can be calculated as:

$$T = \overline{m}^T - R\overline{d}^T \quad (9)$$

E. Convergence Criteria

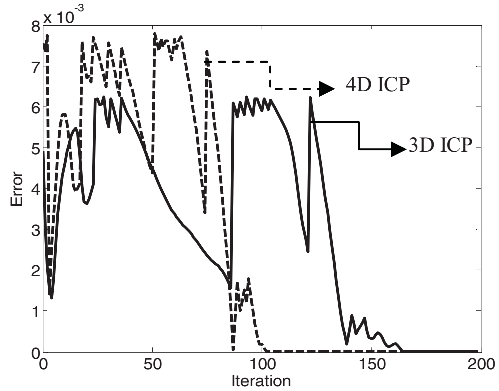
We establish three separate criteria for convergence of the 4D ICP iteration. First, we use a measure called the association stability. Association stability(S) is defined as the number of points that changed their paired points in the previous iteration of the ICP algorithm. A large value of S indicates that the point association is not stable and a small or zero value indicates that the point pairing has stabilized. Secondly we use the convergence of number of points associated during the NNS search. Second convergence criterion used is the change in error, $\Delta\varepsilon$. 4D ICP algorithm is terminated when the following three measures converge:

a) Error value: $\Delta\varepsilon \rightarrow 0$
b) Number of associated new points: $\Delta N \rightarrow 0$
c) Association stability measure: $S \rightarrow 0$.

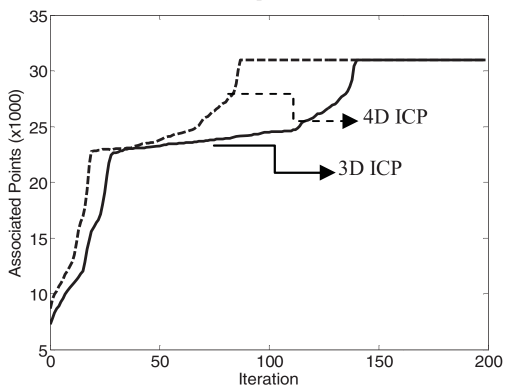
IV. Experimental Results

A. Known 6DOF Transformation Point Cloud Segments Registration

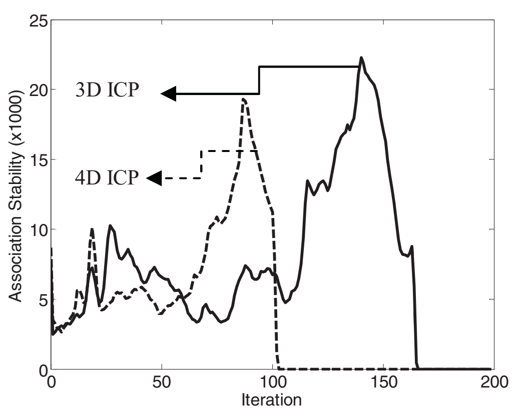
This experiment compares registration speed between 3D ICP and 4D ICP for two point clouds whose registration transformation is known a priori. Both algorithms were applied on the map obtained from the mobile mapping robot [13]. The same point cloud has been transformed to a new viewpoint at 6DOF. New view position is selected with 10° off around both Y and Z axis from the original space. Translation is selected as distance 2.46, 2.612 and 0.347 about X, Y, Z axis respectively. Error comparison and associated point number comparison are shown in Figure 6(a) and Figure 6(b). Association stability is shown in Figure 6(c) to illustrate convergence of the process. The 4D ICP complete registration after 102 iterations and the traditional 3D ICP converges after 164 iterations. This illustrates that 4D ICP algorithm converges faster than 3D ICP because 4D nearest point search provides more accurate point association. Merged color point cloud about building is shown in Figure 7.



(a) Mean square error



(b) Number of associated points



(c) Stability Metric

Figure 6. Evolution of error metrics for 4D ICP and 3D ICP algorithms

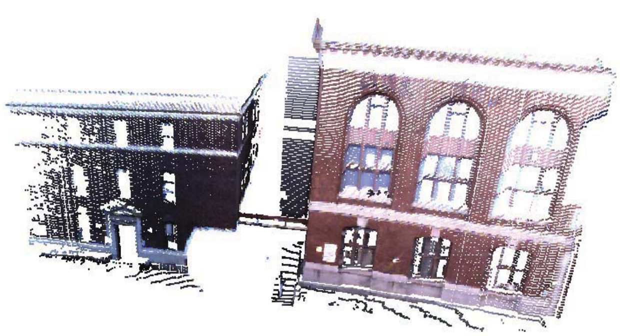


Figure 7. Map after registration

B. *Large Area Point Clouds Registration with Unknown Transformations*

3D ICP and 4D ICP algorithms have been applied to construct an outdoor map. Color point clouds taken from 8 different places have been registered pair-wise to construct the map. Figure 8 shows the aerial view of the mapped region. This scene includes trees, road, electrical poles and buildings. Figure 9 shows the registered maps and the position of mobile robot. Map segments generated from two consecutive vantage points are registered sequentially. After 3D range data has been normalize by scanner range, the search radius in k-d tree is set as 0.0094 for the 3D ICP problem. The hue value has been normalized from 0.0 to 1.0, hue filter range is set to be 0.15 and the hue weight as 0.0023 (approximately 25% of 3D search range). Table 1 shows the evolution of error and the number of iterations required to register the map segments.

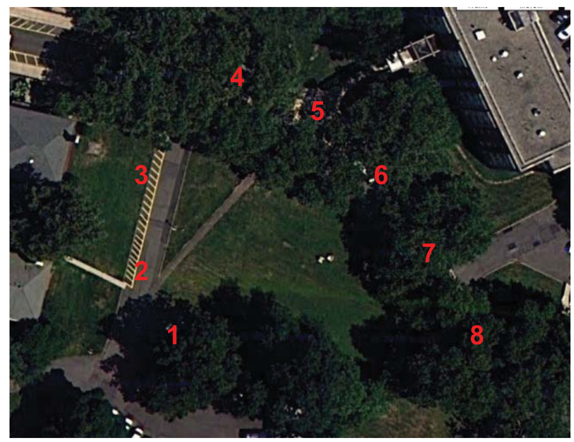


Figure 8. Satellite image of outdoor mapping area and vantage positions

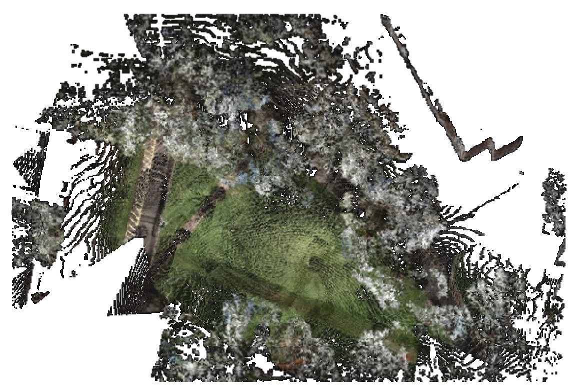


Figure 9: Top view of map generated with eight sequentially registered map segments

TABLE I
COMPARISON OF ERRORS AND ITERATIONS

	3D ICP Iterations	4D ICP Iterations	3D ICP Error	4D ICP Error
2	45	35	0.0052646	0.0053503
3	54	44	0.0058086	0.0060067
4	77	54	0.0002445	0.0018108
5	49	43	0.0006499	0.0019955
6	66	59	0.0010315	0.0011188
7	73	69	0.0008080	0.0008052
8	99	95	0.0004273	0.0004371

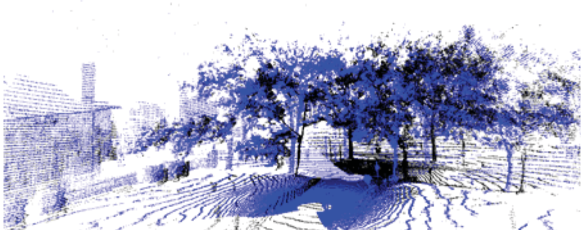
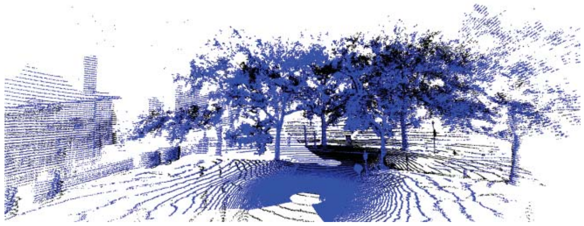


Figure 10: Point cloud map generated from vantage points 3 (blue) and 4 (black) before registration



(a) Black data points originated vantage point 4 and blue data points from vantage point 3.

(b) Coordinate data and color data from both the vantage points

Figure 11: Color point cloud map generated from two vantage points after registration.

4D ICP is seen to require less number of iterations than traditional 3D ICP. This multiple map segments sequential registration experiment illustrates the effect of adding the hue-dimension to the registration progress for large scale map construction. For instance, position 3 and 4 acquired point clouds have been shown in Figure 10 before registration, registered point clouds are shown in Figure 11, Figure 11(a) describes two different point clouds with two different colors, point cloud at position 4 (black) has been registered into position 3 point cloud (blue). Combined point clouds with color are shown in Figure 11(b).

V. Conclusion

A Hue assisted 4D Iterative Closest Point algorithm that uses both the coordinate and hue information to merge map segments is described in this paper. The 4D ICP works without the need for position and orientation information. A building data set and large-scale outdoor point cloud map has been registered using 4D ICP. Use of the hue value to assist the point association and error minimization is shown to be effective during the ICP iteration schemes. Higher dimensional point association based on weighted hue and range data leads to more accurate point matching, faster convergence of ICP process.

References

[1] S. Thrun, "Robotic Mapping: A Survey", Exploring artificial intelligence in the new millennium, Morgan Kaufmann Publishers Inc, pp 1-35, 2003.

[2] PJ. Bsel, "A Method for Registration of 3D Shapes", IEEE Trans on Pattern Analysis and Machine Intelligence, Vol. 14, pp239-256, 1992

[3] K. S. Arun, "Least Square Fitting of Two 3D-Point Sets", IEEE Trans on Pattern Analysis and Machine Intelligence, Vol.9 No.5, pp698-700, 1987.

[4] J. Timotee, "Fast ICP Algorithms for Shape Registration", Pattern Recognition, , Springer Berlin, pp 91-99, 2002.

[5] S. Thrun, "Exploration and Model Building in Mobile Robot Domains", IEEE International Conference on Neural Networks, Vol.1 , pp 175-180,1993, San Francisco, USA.

[6] A. Nuchter, "6D SLAM with Approximate Data Association", IEEE International Conference on Robotics and Automation, pp242-249, 2005, Barcelona, Spain.

[7] A. Nuchter, "Catched k-d tree Search for ICP Algorithms", 6th International Conference on 3-D Digital Imaging and Modeling, 2007.

[8] S. Rusinkiewucz, "Efficient Variants of the ICP Algorithm" 3rd International Conference on 3-D Digital Imaging and Modeling, pp145-152, 2001.

[9] A. Lorusso, "A Comparison of Four Algorithms for Estimating 3D Rigid Transformations", British Machine Vision Conference, 1995

[10] C. Robertson, "Parallel Evolutionary Registration of Range Data", Computer Vision and Image Understanding, Vol 87, pp 39-50, 2002

[11] S. Druon, "Color Constrained ICP for Registration of Large Unconstructed 3D/Color Data Sets", IEEE International Conference on Robotics and Automation, pp249-255, 2007.

[12] H. Andresson, "Vision Aided 3D Laser Scanner Based Registration", roc. European Conference on Mobile Robots: ECMR, pp192-197, 2007.

[13] B. Gebre, H. Men, K. Pochiraju, "Remotely Operated and Autonomous Mapping System(ROAMS)," 2nd Annual IEEE International Conference on Technologies for Practical Robot Applications, Woburn, MA, 2009

[14] A. Makadia, E. P, Iv, K. Daniilidis, "Fully Automatic Registration of 3D Point Clouds", Proceedings of the 2006 Computer Society Conference on Computer Vision and Pattern recognition, pp1297-1304, 2006

[15] A.G. Chibunichev, A.B. Velizhev, "Automatic Matching of Terrestrial Scan Data Using Orientation Histograms", The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XXXVII, Beijing, 2008.

[16] J.H. Joung, K.H. An, J.W. Kang et al, "3D Environment Reconstruction Using Modified Color ICP Algorithm by Fusion of a Camera and a 3D Laser Range Finger", The 2009 IEEE International Conferrnce on Intelligent Robos and Systems, St. Louis, USA, 2009.

[17] A.E. Johnson, S.B. Kang, "Registration and Integration of Textured 3D Data",Proceedings of International Conference on Recent Advances in 3D Didital Imaging and Modeling, pp234-241, Ottawa, Canada, 1997.

[18] H. Men, K. Pochiraju, "Hue Assisted Registration of 3D Point Clouds", ASME 2010 Interaional Design Engineering Technical Conference, Montreal, Canada, 2010.

[19] H. Andreason, A.J. Lilienthal, "6D Scan Registration using Depth-interpolated Local Image Features", Robotics andAutonomous Systems, Vol.59, 2010, pp157-165.

[20] D. Hähnel, W. Burgard, Probabilistic matching for 3d scan registration, in: Proceedings of the VDI-Conference Robotik, 2002.

[21] A. Makadia, E. P, Iv, K. Daniilidis, "Fully Automatic Registration of 3D Point Clouds", Proceedings of the 2006 Computer Society Conference on Computer Vision and Pattern recognition, pp1297-1304, 2006

[22] A.G. Chibunichev, A.B. Velizhev, "Automatic Matching of Terrestrial Scan Data Using Orientation Histograms", The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XXXVII, Beijing, 2008.

[23] B. Huhle, M. Magnusson and W. Straber et al., "Registration of Colored 3D Point Clouds with a Kernel-based Extension to the Normal Distributions Transform", IEEE International Conference on Robotics and Automation, Pasadena, CA, USA, May 19-23, 2008.