3D Scan Registration Based Localization for Autonomous Vehicles – A Comparison of NDT and ICP under Realistic Conditions

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***Abstract*—Iterative closest points (ICP) and normal distributions transform (NDT) are popular 3D point cloud registration algorithms, which have been widely used in mapping and 3D reconstruction. These algorithms provide robust methods for self-localizing an autonomous vehicle by registering real-time 3D-scans to a prior map. However, urban and suburban environments are continually changing, resulting in significant differences that impact registration algorithms. These temporal changes occur over varying time-scales, and include dynamic and ephemeral objects (such as parked cars), seasonal changes (vegetation, snow, dust), and human impacts such as construction. It is critical that a self-localization method be robust to these and other real-environment changes. Furthermore, the computational complexity of the algorithm and its stability and ability to process data in real-time when faced with such adverse conditions are important. In this paper, we present an empirical comparison of NDT and ICP and their performances for autonomous vehicle localization through a set of realistic field tests conducted in the state of Michigan over many months spanning the summer, fall, and winter months. The test sites include the campus of Michigan State University and the University of Michigan's MCity Test Facility, which is a professional purpose-built proving ground for testing autonomous vehicles and technologies. Our tests indicate that NDT possesses a better ability to handle realistic adversity conditions such as static and dynamic environmental changes, as well as being more computationally efficient.**

Keywords—ICP, NDT, Autonomous driving, localization, 3D registration

I. INTRODUCTION

Self-driving vehicles must sense their environments, localize themselves, plan routes and apply vehicle control to traverse these paths. Of these tasks, localization is critical as all other key sub-systems rely either fully or partially on the performance of the localization algorithm. In particular, the update rate for localization has to be faster than the other components. Arguably, the two most popular localization algorithms based on 3D point cloud registration are iterative closest point (ICP) and normal distributions transform (NDT) algorithms[1]–[3]. Although these methods have been studied in numerous prior efforts, a thorough comparison of their performance under realistic conditions for autonomous driving applications has not been conducted. Magnusson *et al.* conducted a comparison of ICP and NDT based on 3D mapping field experiment in mine tunnels [4]. However, there is a need to evaluate the robustness of these popular algorithms under diverse environmental changes typical of vehicular roadways. For example, a reference map developed under the favorable conditions of a clear summer day will need to be registered to in different seasons, such when the leaves have fallen in the autumn, and when the road and other major landmarks are covered with snow in the winter. Additionally, temporary or permanent structural changes to the road or surrounding structures should also not prevent successful registration. Temporary or ephemeral objects (such as parked vehicles) also pose a challenge to registration and precise localization as they may occlude and/or create features. Furthermore, localization must be achieved in real-time with low-latency. All these aspects of localization represent important and practical considerations in selecting a solution for autonomous driving where safety is of a paramount importance.

In this paper, we present an evaluation and comparison of NDT and ICP and their performances for autonomous vehicle localization under diverse environmental conditions. We have tested other variants of ICP and NDT, but considering the essences of the algorithms are similar and the space of this paper is limited, we only show the result of the comparison between standard ICP and NDT. Our study is based on a set of realistic field tests conducted in the state of Michigan over nine months spanning the summer, fall, and winter. The test sites include the campus of Michigan State University and the University of Michigan's MCity Test Facility, which is a professional purpose-built proving ground for testing autonomous vehicles and technologies. The reference maps were developed professionally by a mapping company for all sites included in our study. A high precision positioning system capable of providing centimeter-level precision was employed to provide near-groundtruth precision for the purpose of evaluating the true performance of both the ICP and NDT algorithms. Our extensive tests show that NDT possesses better ability to handle realistic adversity conditions such as static and dynamic environmental changes and is more computational efficient.

The remainder of the paper is organized as follows: Section II briefly covers the basic introduction to ICP and NDT that provided the foundation for this work. Section III describes the main constraints and unique challenges for the 3D scan registration based localization. Section IV presents the results of the experiments performed over many months spanning the summer, fall, and winter months. Section V concludes and summarizes the paper.

II. BACKGROUND AND RELATED WORK

A. ICP

The ICP algorithm iteratively minimizes point to point distances between an input scan and a reference point cloud [1], [2]. In each step, the closest reference point to each scan point are selected, and the rotation and translation, $\mathbf{R}$ and $\mathbf{t}$ respectively, are calculated that minimize the sum of squared distances:

$$E(\mathbf{R},\mathbf{t}) = \sum_{i=1}^{M}\sum_{j=1}^{N} w_{i,j} \,\| \mathbf{m}_i - (\mathbf{R}\mathbf{n}_j + \mathbf{t}) \|^2,$$

where $\mathbf{m}_i$ and $\mathbf{n}_j$ are the i_{th} and j_{th} point vector from two point sets *m* and *n*. *M* and *N* are the number of points in the set *m* and set *n*, respectively. $w_{i,j}$ are the weights for a pair of matching points. If $\mathbf{m}_i$ is the closest point to $\mathbf{n}_j$, then $w_{i,j}=1$, otherwise $w_{i,j}=0$.

B. NDT

Instead of using the individual points of the point cloud as in ICP, NDT transforms the set of 3D data-points residing within a voxel into a normal distribution [3]. For voxel *k*, an average $\mathbf{p}_k$ and covariance matrix $\sum_k$ are calculated as follows;

$$\mathbf{p}_k = \frac{1}{M_k}\sum_{i=0}^{M_k-1}\mathbf{x}_{ki}$$

$$\Sigma_k = \frac{1}{M_k}\sum_{i=0}^{M_k-1}(\mathbf{x}_{ki}-\mathbf{p}_k)(\mathbf{x}_{ki}-\mathbf{p}_k)^t,$$

where, $\mathbf{x}_{ki} = (x_{ki}, y_{ki}, z_{ki})^t$, $i = 0 ... M_k - 1$ represents the i_{th} point vector of data-point *i* residing in voxel *k*, and M_k is the number of points in voxel *k*. For points in the input scan $\mathbf{X} = \mathbf{x}_i, (i = 0...N - 1)$, the transformation equations are given as follows:

$$\mathbf{x}_i' = \mathbf{R}\mathbf{x}_i + \mathbf{t}'$$

where $\mathbf{R}$ is a rotation matrix parameterized by Euler angles α, β, γ, and $\mathbf{t}' = (t_x, t_y, t_z)^t$ is the translation vector. The registration is a parameter search problem that finds the best transformation $\boldsymbol{T} = (\mathbf{R}, \mathbf{t}')$ for the input scan to match the reference scan. The measure function (some paper also called it the *negative-score (-score) function* [3]) is defined as follows:

$$E(\mathbf{X},\boldsymbol{T}) = -\sum_{i}^{N-1}\exp\frac{-(\mathbf{x}_i'-\mathbf{p}_i)\Sigma_i^{-1}(\mathbf{x}_i'-\mathbf{p}_i)}{2},$$

where $\mathbf{p}_i$ and $\sum_i$ are the corresponding average and covariance matrix of the reference scan. Newton's method is used to finding the best transformation $\boldsymbol{T}$ to minimize $E(\mathbf{X},\boldsymbol{T})$ [5].

III. CONSTRAINTS AND CHALLENGES FOR 3D SCAN REGISTRATION BASED LOCALIZATION

Autonomous driving imposes a unique set of challenges to 3D-scan registration based localization. First is the major differences between the reference 3D map and the real-time 3D point-cloud scans captured by the vehicle. Changes in urban and suburban environments must not prevent correct alignment between scans and a reference map. Second is the need to perform low-latency, real-time localization. Unlike mapping and reconstruction, which can be done offline, the autonomous driving system must make real-time decisions based on vehicle localization. Latency in localization will result in reduced performance. Third is the need to eliminate all gross errors, as these will have large deleterious effects on the other upper level modules that depend on localization.

A. The ability to handle environmental changes

High-resolution reference maps may be updated much less frequently than changes to the environment. These changes can be divided into two categories: static and dynamic.

- *Static changes* refers to semi-permanent alterations of the environment since the map was created. These include decaying leaves, snow cover, structural changes to buildings and landmarks, construction of new facilities, and parked cars on the roadside.
- *Dynamic changes* are the moving objects during an actual trip that are not included in the reference 3D map, including passing vehicles, pedestrians, and bicycles.

Localization requires correctly registering a Lidar scan to the prior map despite both static and dynamic changes.

B. Real-time requirement

The real-time requirements are due to the need for low-latency in vehicle control. At typical urban speeds of 15~35 mph, a latency more than 100ms will result in meter level uncertainty for the vehicle position which may cause safety issues. In addition, registration must keep up with the scanning Lidar, which typically operates at 10Hz.

C. No Gross Errors

Gross errors in localization during autonomous driving could cause fatal accidents. Thus it is important to assess the reliability and accuracy of ICP and NDT if they are to be used for localization.

IV. EXPERIMENTS AND RESULTS

A. Experimental Platform

The experimental platform used in this study is a modified, drive-by-wire Lincoln MKZ. The vehicle is equipped with a Velodyne PUCK (VLP-16) 16 line LiDAR, and a NovAtel PwrPak7 GNSS Inertial Navigation System to collect the near-groundtruth data for analysis. A Core i7 CPU runs Ubuntu and Robot Operating System (ROS).

B. Test Site

Figure 1. Test sites. Left: MCity at Ann Arbor. Right: West Circle Drive at the campus of Michigan State University in East Lansing

Figure 1 shows the two test sites used for this study. One is the University of Michigan's MCity Test Facility in Ann Arbor, a purpose-built proving ground for testing autonomous vehicles in simulated urban and suburban driving environments. Another is West Circle Drive, a traffic hub in Michigan State University main campus.

C. Parameters and runtime for ICP and NDT

For both ICP and NDT a number of parameters can be tuned to adjust performance. In this paper, we tested the most influential parameters and evaluated the localization with mean absolute error (MAE), and computational time. The test route is a path in the MCity of length 350 meters and vehicle speed of 17mph.

Parameters for ICP are: Reference map resolution, transformation difference threshold and Euclidean fitness threshold. Reference map resolution is defined as the number of points within a $1m \times 1m$ plane. The transformation difference threshold is the minimum distance below which iterative convergence will terminate. Euclidean fitness threshold represents the maximum allowed Euclidean error between two consecutive steps in the ICP loop before convergence, and Euclidean error is the sum of the Euclidean distances between correspondences divided by the number of correspondences [6].

Parameters for NDT are: Reference map resolution, voxel size, transformation difference threshold and maximum step size. The voxel size defines the voxel resolution of the internal NDT grid structure. The transformation difference threshold has the same meaning as in ICP. Finally, the maximum step size defines the maximum step length in the optimization process[7].

TABLE I. THE PERFORMANCE FOR NDT AND ICP CORRESPONDING TO DIFFERENT REFERENCE MAP RESOLUTION

	NDT		ICP	
Reference Map Resolution (points/ m^2)	Localization MAE error(m)	Average time for registration (ms)	Localization MAE error (m)	Average time for registration (ms)
9	0.3391	5.814	**0.1250**	**68.726**
36	0.0618	9.648	0.1167	203.549
121	**0.0473**	**10.404**	-	-
400	0.0470	11.824	-	-

*For ICP, the computing time will be larger than 2 seconds for each registration step if the map resolution equals 121 points/ m^2 or higher, therefore, the results are not listed in the TABLE.

TABLE I shows the performance for NDT and ICP corresponding to different reference map resolution. The localization mean absolute error (MAE) for NDT is significantly smaller than ICP, except when the map resolution is 9 points/ m^2 . For NDT, although the localization accuracy between map resolution equals 36 points/ m^2 and 121 points/ m^2 respectively is close, the computing time for map resolution equals 36 points/ m^2 is shorter, therefore, 36 points/ m^2 map resolution is considered as the best for NDT. For ICP, the best map resolution is 9 points/ m^2 because the computing time for other map resolution does not meet the real time requirement. In all tables the rows highlighted in bold are either the best values or the values that we selected for our tests.

TABLE II and TABLE III shows the MAE localization error and the average computational time for each registration with different parameter settings of NDT and ICP. ICP is much more time consuming than NDT because the NDT matching time is $O(N)$ where N is the number of input scan points [5]. The original ICP's complexity is $O(N^2)$, and using kd-tree to establish closest point relationships (this is the most popular ICP and also the one tested in this paper) reduces the complexity to $O(N \log N)$ [8].

TABLE II. DIFFERENT ICP PARAMETER SETTINGS AND THE CORRESPONDING PERFORMANCE

	Value of the parameters	Localization MAE Error (m)	Average time for registration (ms)
Transformation difference threshold (m)	0.005	0.1240	69.169
	0.01	**0.1236**	**68.723**
	0.02	0.1342	67.968
Euclidean fitness threshold (m)	0.05	0.1212	69.387
	0.1	**0.1241**	**68.716**
	0.2	0.4137	68.2459

TABLE III. DIFFERENT NDT PARAMETER SETTINGS AND THE CORRESPONDING PERFORMANCE

	Value of the parameters	Localization MAE Error (m)	Average time for registration (ms)
Voxel size (m)	0.5	0.0525	11.799
	1	**0.0463**	**11.088**
	2	0.0501	9.780
Transformation difference threshold (m)	0.005	0.0473	13.160
	0.01	**0.0452**	**11.090**
	0.02	0.0532	9.986
Maximum step size (m)	0.05	0.0472	12.937
	0.1	**0.0467**	**11.082**
	0.2	0.0581	9.874

Figure 2. Same location in different seasons with static changes. Upper: Aug 2017 (mapping data). Bottom left: Dec 2017. Bottom right: March 2018.

Note that these experiments were done at the MCity facility, which is a synthetic test site. Except for heavy snow or rain, the static environment at MCity facility was stable without much change. And during the tests, there were no other moving objects. This is the ideal condition for testing the performance of registration without any influence from other factors. Therefore, the performance results listed here can be treated as the benchmark for the two algorithms.

D. Evaluation for environmental changes

1) For static changes: The reference maps were developed professionally by CARMERA [9], a mapping company, for all sites included in our study. The mapping data used in this experiment was collected in West Circle Drive, Michigan State University main campus, during late July and early August 2017. To evaluate ICP and NDT under environmental changes, we conducted two series of autonomous path-following experiments in December 2017 and March 2018; and then calculated the Euclidean distance between the localization results and the pre-planned path we set for the vehicle to follow. The vehicle control, path planning algorithm and the pre-planned path for the two experiments at different time are all the same. Note that the environments in the two experiments are both different from the one when the map was built. When compared to summer when the map was constructed, (i) the December test was conducted with snow covering the whole surrounding environment, (ii) both the December and March tests were conducted when there were no leaves on the trees, and (iii) in March there was fewer grass coverage on the ground. Figure 2 depicts the same position in the different season disscussed above with static changes.

TABLE Ⅳ shows the comparison of NDT and ICP performance under static environmental changes. The NDT based localization MAE deviation from the pre-planned path for the December 2017 test and March 2018 test is 0.0661m and 0.0403m respectively. While the ICP based localization error is an order of magnitude worse than the NDT based method. This result demonstrates that NDT is better able to handle environmental changes.

2) For dynamic changes: We evaluated the algorithms' performance under dynamic changes by driving the vehicle around West Circle Drive when there were a significant number of vehicles and other dynamic objects. The size of the moving objects can influence the extent of the impact on the localization algorithm. Figure 3 shows an extreme example where a large bus blocks nearly half of the field of view. The average localization MAE error for NDT during this time was 0.089m vs. 0.3m for ICP.

TABLE IV. COMPARISON OF NDT AND ICP IN PERFORMANCE UNDER STATIC ENVIRONMENTAL CHANGES

Method / Test Time	NDT based localization MAE deviation from the pre-planned path (m)	ICP based localization MAE deviation from the pre-planned path (m)
Dec 2017	0.0661	0.2341
Mar 2018	0.0403	0.1636

E. The impact of the vehicle speed

We tested different levels of speed from 5mph to 30mph at MCity with a 1km long route. We classified the speed into three levels, level 1 is 5~10 mph, level 2 is 15~20 mph, level 3 is 25~30mph. For NDT, localization MAE errors are 0.0406m, 0.0542m and 0.0514m for speeds 1, 2 and 3 respectively. For ICP, the pattern is similar with corresponding MAE errors of 0.1074m. 0.1264m and 0.1311m.

Vehicle speed impacts the accuracy of the initial guess of pose for each step of the registration. This guess is based on

Figure 3. Example of dynamic changes of the environment. The points inside the blue bounding box in the left figure correspond to the passing bus in the right figure.

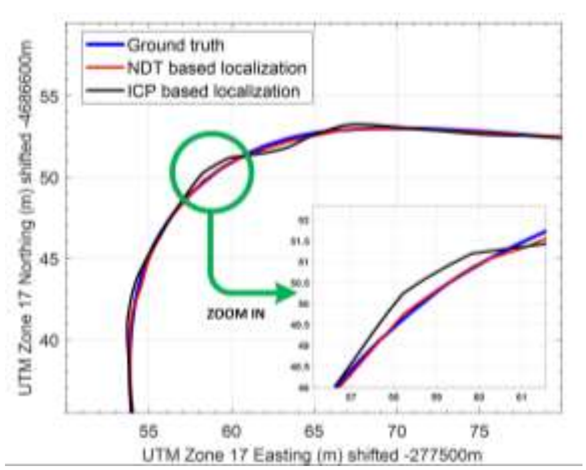

Figure 4. Comparison between NDT and ICP during the turning.

the previously estimated pose. If the vehicle drives faster, the difference the error in the initial guess will be larger, which makes the scan registration more challenging. NDT is able to converge from a larger range of initial values than ICP as explained in [4], and our observation is that for speeds up to 30 mph, NDT achieves smaller localization error than ICP.

F. Analysis for other situations that would cause higher localization error

1) Turning segment: Initial guess for 3D scan registration is important. In autonomous driving localization, the initial guess is provided either by the pose from the previous registration step or the usage of vehicle motion/inertia data. In this paper, we only discuss the former one. Therefore, when the vehicle is making a turn, as compared to following a straight road, there would be not only a translation but also a rotation between the actual input scan and the reference map. Hence, under a turn, there would be a higher probability of registration error. Figure 4 depicts the comparison of NDT and ICP localization over one of the turning segments at MCity. The comparison is shown in terms of Universal Transverse Mercator (UTM) coordinates when the average vehicle speed at this segment of the road was around 15mph. (Because the coordinate's absolute UTM value is usually too large and inconvenient to show in the figure, shifts in both UTM Easting and Northing are applied to make the figure easier to read.) The NDT based localization MAE error during this turn is 0.0710m, which is very much within the designated path, while for ICP the localization MAE error during this turning segment is 0.1917m. Error during turning is generally higher when the turning radius is smaller and there are fewer localization features, however this is not always the case.

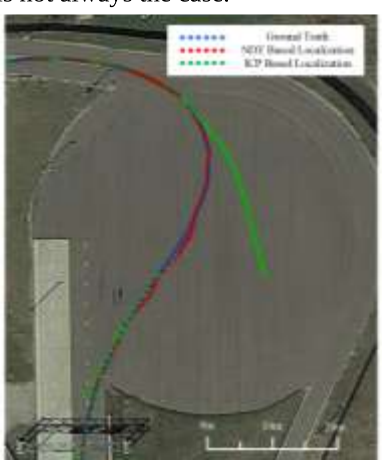

Figure 5. Comparison between NDT and ICP based localization in an empty space

2) Places where there are fewer vertical features: Vertical features (e.g., buildings, trees and fences, etc.) is especially important for 3D scan registration based localization. Registration algorithms may fail when the vehicle moves into an empty space with too few or no vertical features. In MCity, there is a large circular empty region with 40 meters in radius that has very few vertical features around. Figure 5 depicts the comparison of the ICP and NDT based localization with regard to the ground truth; the vehicle speed in this scenario is 17mph. The blue dots represent the ground truth position, the red and green dots stand for the position calculated from NDT and ICP, respectively. As shown in Figure 5, ICP completely failed in this test scenario while NDT was able to maintain an overall acceptable performance. Nevertheless, and despite the consistent superior performance of NDT under other tests, here, even NDT suffered from relatively much higher error when compared to other test scenarios in places with more salient vertical features. The largest NDT localization error in this region is 1.1166m, and its MAE error for this region is 0.2544m; meanwhile, and as mentioned above, ICP completely failed. In this situation, NDT was still able to make use of the curbs and other vertical features far away in this situation; this is due to NDT's use of voxels instead of individual points, which increases the relevance of vertical features in the registration process. By contrast, for ICP the number of points in vertical features are dwarfed by the number of ground points, resulting in a less accurate solution (if one is even found). This experiment demonstrates that NDT is more robust and with lower probability to have gross errors than ICP under sparse vertical features.

V. CONCLUSIONS

We have evaluated the performance of ICP and NDT for autonomous vehicle localization by registering real-time scan to a prior 3D point-cloud map. With sufficient number of vertical features, both methods perform robustly, although NDT runs much faster than ICP, and had rather significantly smaller localization error. Compared to focusing on individual points in ICP, the probabilistic voxelization representation makes NDT be able to obtain the big picture of the environment instead of details. Therefore, the NDT based method possesses better ability to handle realistic variations occurring over the course of nine months including both static and dynamic environmental changes.

ACKNOWLEDGMENT

Special thanks to Ethan Sorrelgreen and other colleagues from CARMERA [9] who led the development of the 3D point-cloud maps and related data used as our primary reference for this study.

REFERENCES

[1] P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 14, no. 2, pp. 239–256, Feb. 1992.

[2] Y. Chen and G. Medioni, "Object modelling by registration of multiple range images," *Range Image Underst.*, vol. 10, no. 3, pp. 145–155, 1992.

[3] P. Biber and W. Strasser, "The normal distributions transform: a new approach to laser scan matching," in *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453)*, 2003, vol. 3, pp. 2743–2748 vol.3.

[4] M. Magnusson, A. Nuchter, C. Lorken, A. J. Lilienthal, and J. Hertzberg, "Evaluation of 3D registration reliability and speed - A comparison of ICP and NDT," in *2009 IEEE International Conference on Robotics and Automation*, 2009, pp. 3907–3912.

[5] E. Takeuchi and T. Tsubouchi, "A 3-D Scan Matching using Improved 3-D Normal Distributions Transform for Mobile Robotic Mapping," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2006, pp. 3068–3073.

[6] http://pointclouds.org/documentation/tutorials/interactive_icp.php.

[7] http://docs.pointclouds.org/.

[8] T. Jost and H. Hügli, "Fast ICP Algorithms for Shape Registration," in *Pattern Recognition*, 2002, pp. 91–99.

[9] https://www.carmera.com/.