

Localization and Mapping by an Improved ICP Algorithm and a Feature-based Alignment Correction Algorithm

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ABSTRACT

This study presented a real-time localization and mapping algorithm that integrates an improved iterative closest point (ICP) algorithm, a feature-based alignment correction algorithm, and a local minimum avoidance mechanism. It started with an investigation of the ICP algorithm. Such a point-based algorithm guarantees a local minimum for the process matching two scans (i.e., maps). However, the local minimum often has a large difference from the desired global minimum. Such an issue is often induced by outliers. A mechanism neglecting some high-leverage outliers was incorporated in every ICP iteration to resolve this issue. Although this process produces an acceptable result, the efficiency and accuracy issues must be addressed. A line-based representation for scans is able to reduce processing time and was therefore adopted in this study. Also, an alignment correction algorithm utilizing line features was proposed to reduce the error of alignment between two matched scans. The derived line-based process produces better results than the original one. Finally, the methods to avoid local minima were described. Although it may be resolved to some degree by neglecting a part of outliers, the process may still converge to a local minimum occasionally. Accordingly, a mechanism for avoiding local minima was integrated into the process to further cope with this issue. The feasibility of the presented algorithm was verified through various experiments.

Keywords: localization and mapping, ICP, feature-based alignment correction, scan matching

結合改良式 ICP 與特徵校正法之定位與製圖研究

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摘 要

本研究提出一套即時定位製圖演算法，結合了改良式 ICP、基於特徵之校準演算法及區域最佳化避免機制。雖原始 ICP 保證兩張點狀地圖之疊合達區域最佳化，然與所尋求之廣域最佳化有所差異。此問題常由離群值造成，故本研究採用忽略高影響性離群值之機制進行改善。此外改採線段表示地圖，可提升程序效率與精確度，另運用線段特徵值進行校正，有效修正地圖疊合結果之誤差。所提出基於線段之程序，比原基於點之程序產出較佳結果。最後，提出一套區域最佳化避免機制，進一步解決區域最佳化問題。所提出演算法之可行性，已透過實驗進行驗證與展示。

關鍵詞：定位與製圖，ICP，基於特徵值之校正，地圖疊合

I. INTRODUCTION

Localization and mapping is a technique utilized in the research of autonomous robots. It provides a robot with a means to incrementally building the map of its environment while simultaneously estimating its pose (i.e., orientation and position) on this map [1-4]. The single consistent map being built can be described as the global map, with respect to a sequence of local maps created at different locations.

A local map is often referred to as a local scan. The local scan may be represented in any format, as long as the created scan is consistent in illustrating the environment surrounding the robot at every scanning location. For example, the point-based and the line-based representations were adopted in this study for particular uses. For building a local map, the robot uses its onboard sensors (e.g., ultrasonic and laser ranging devices) to collect information regarding the environment relative to its current location.

The general concept of localization and mapping is straightforward. Supposing that the robot's transformation (i.e., a rotation and a displacement) at the time of taking the current scan relative to the one at the time of taking the previous scan is determined, the mapping process can be carried out by directly applying such a transformation to either scan and thus allowing it to be matched and aligned with the other. That is to say, the transformation converting one pose of the robot to the other is the same one aligning one scan with the other. Therefore, on the premise that the localization problem is solved (i.e., the transformation is known), the mapping problem will be solved as well. However, the transformation that drives the robot toward its new pose is often inaccurate due to the odometry errors accumulated over time. In consideration of this situation, solving the localization problem beforehand may be infeasible, and the transformation may need to be determined from the other perspective, that is by solving the mapping problem (i.e., how to match and align one scan with the other). This approach will require determining the correspondence between two scans being matched. Since the two problems (namely, the localization and the mapping problems) are tightly coupled, they can be combined and regarded as one single study—localization and mapping.

The procedure following the mapping process that matches and aligns two scans is merging them into a single one. Such a single scan represents the environment of the robot better than either of the local scans. As the robot takes scans along its path while moving, its trajectory and the global map are constructed incrementally.

Without regard to the merge of the two matched scans, localization and mapping can be simply regarded as the scan matching study in this context. However, while the localization and mapping concept is straightforward, coping with the issues regarding the process of scan matching is much more complex. For instance, a majority of proposed algorithms in the literature determining the transformation that matches two scans are fairly difficult and their results greatly depend on the conditions of the environments. An algorithm that is suited to the particular requirement of an environment may not necessarily be suited to others. Another issue to consider is that there is almost always an efficiency-accuracy tradeoff in any algorithm, especially the ones being aimed at real-time operations. For the scan matching process, it is the tradeoff between the process efficiency and scan matching accuracy, and it depends on different conditions and requirements.

The primary task of this study is to develop a real-time ranging sensor-based localization and mapping algorithm that addresses the two common issues:

- 1) resolving the local minimum issue of scan matching, and
- 2) improving accuracy and efficiency.

A scan matching technique, namely, the iterative closest point (ICP) algorithm, is considered to be a benchmark for the algorithms and mechanisms to be developed in this study. Although such a technique is fairly old, it is still worth investigating because of its great efficiency for use in real time.

The laser ranging system used in this study is a UTM-30LX. Such a system was reported to produce stable measurements with little influence from the reflectance and colors of objects. It utilizes the 905-nanometer infrared laser. For every scanning cycle, it scans counterclockwise in a 270-degree fan-shaped area. Fig. 1 illustrates a notional representation of the scanning area. The guaranteed scanning range covers from 0.1

to 30 meters. The maximum range is 60 meters (by degrading its performance). The system estimates the distances between objects and itself for 1080 angular steps (with a total of 1081 measurements) covering the 270-degree area. By processing the distance measurements, the environment information around the system can be obtained. The time needed to complete the scanning cycle once is 25 milliseconds (approximately 24 milliseconds to scan and 1 millisecond to synchronize the data) without regard to that to transmit and to process the data [5].

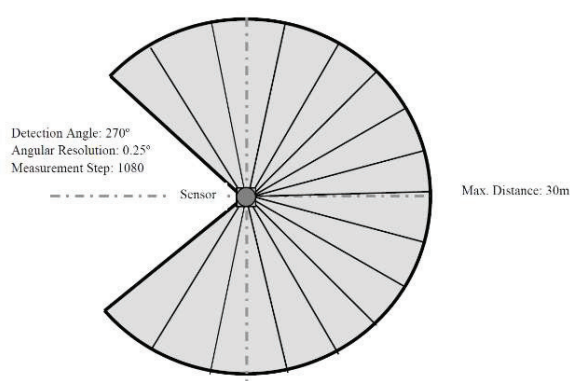


Fig. 1. The UTM-30LX scanning area [5]

The rest of this paper is organized as follows. Section 2 describes the related studies in the literature that sought improvements in either efficiency or accuracy, and in adapting to different environment conditions. Section 3 investigates the ICP algorithm and improves it for real-time processing of localization and mapping. Section 4 presents a feature-based alignment correction algorithm to cope with the issue of large accumulated estimation errors associated with localization and mapping using the ICP algorithm. Section 5 proposes a local minimum avoidance mechanism. The final section provides a summary of the contributions of this study and also discusses some limitations and considerations for future work.

II. RELATED WORKS

Some localization and mapping studies, that sought improvements in either efficiency or accuracy, and in adapting to different environment conditions, are introduced as follows.

In the studies by Amigoni, Gasparini, and

Gini [6, 7], a local scan is a collection of line segments obtained by processing the distance measurements of a two-dimensional (2D) laser sensor. The resulting global map is a 2D line-based geometric map built by post-processing the local scans (i.e., not processing in real time). The integration of the two scans will be based on the geometrical information within the scans. Specifically, the angle between each pair of line segments is regarded as a geometrical landmark (i.e., feature). The integration process is thus characterized by the comparison between such geometrical landmarks of the two scans being matched. When the difference between two angles is less than a specified threshold, they are considered equal. Similarly, when the distance between two points is short enough, they are considered to coincide.

A sonar-based algorithm was presented for a robot operating in an unknown and unstructured environment [8]. The algorithm utilizes the sonar measurements to construct a multileveled description for the environment, where the local scans are described using the probability profiles to discriminate between the occupied and empty areas. The global map is built by integrating multiple local scans from different points of view and is used for navigation and path planning.

Similarly, a probabilistic approach was adopted [9]. The distance measurements are converted by a sensor model into a sequence of grid statuses forming a local scan. The global map is then updated by using the Bayes' theorem. As for the robot's pose, it is estimated by utilizing the incremental maximum likelihood (ML) scan matching. By integrating the distance measurements gathered from the laser and sonar sensors, both mapping accuracy and obstacle detection were reported to be improved.

A map optimization algorithm was developed [10] to cope with the initially poor estimate of the map. It utilizes a variant of the stochastic gradient descent (SGD) on an alternative representation of the state space. The algorithm was reported to have good stability and computational properties.

An approach combining two existing algorithms, namely, the polar scan matching (PSM) algorithm and the point-to-line iterative closest point (PLICP) algorithm, was proposed [11] to resolve the issue due to low-quality distance estimates from a small ranging device

and to offer robust scan matching results in different types of environments that are human-made.

A design focusing on feature matching was developed for map building [12]. Such a design uses an improved linear binary relation algorithm to determine the similarity in the line features between two adjacent maps and to establish a matching degree matrix of line features. After a rough match between two maps is performed, a region search optimization algorithm and a random-walk method are used to improve the orientation and position estimates, respectively.

A method that uses progressive scan matching was proposed to promote the pose tracking performance [13]. The orientation and position estimates are generated separately to enhance the process efficiency and accuracy. It was reported that applying progressive iteration in pose estimation is able to ensure achieving a certain precision.

An adaptive perception system was developed [14] to adapt to different types of environments, namely, the outdoor and indoor environments. Such a system classifies the operational environments before applying corresponding systems to conduct localization and mapping. The classification of operational environments is conducted by utilizing image classification techniques. The features in the images are extracted from video imagery and are utilized for training a classification function built by adopting the supervised learning techniques. When operating outdoors, a terrain map utilizing the data collected by the global positioning system (GPS) and the inertial measurement unit (IMU) is used. On the other hand, when operating indoors, a 2D laser-based technique is used for conducting localization and mapping. The indoor local map is first transformed and represented in the global reference frame and then is combined with the outdoor map to generate a global map.

Some studies also focused on reducing memory consumption. For example, a method based on a particle filter was proposed [15] to perform scan matching and to generate a grid map online. Such a method maintains only one single grid map so that the memory being consumed can be limited to a certain degree. Both accuracy and memory consumption were reported to be improved.

III. IMPROVED ITERATIVE CLOSEST POINT (ICP) ALGORITHM

In this section, a scan matching technique, the iterative closest point (ICP) algorithm [16], is investigated and further improved for real-time processing of localization and mapping.

3.1 Point-based Maps

Various types of representations were adopted in the literature to illustrate a 2D map of the environment. Considering the outline of the operating environment and the characteristics of the utilized ranging system, some may adopt a representation utilizing features (e.g., shapes, line segments, and points) to illustrate the corners and walls in indoor environments, while others may adopt one utilizing the occupancy grids to indicate whether a set of square spaces are vacant or occupied in indoor or outdoor environments [17-20].

The information collected by a ranging system (e.g., a laser scanner) typically consists of a series of distance measurements (or estimates). Each of such measurements may be represented by a 2D/3D point (in the Cartesian or polar form) since its direction is known. Considering this fact, it is straightforward to use a point-based map for representing the distance measurements. The map that geometrically describes the outline of an environment of the ranging system (i.e., scanner) is also called a scan. Fig. 2 shows an example of the 2D point-based map (or scan). Fig. 3 shows the actual environment for this particular example.

3.2 The Original ICP Algorithm

As the ranging system (mounted on the mobile robot) consecutively scans the environment during level movements, the localization and mapping process can be conducted by incrementally matching and merging the map with each new scan acquired. The iterative closest point (ICP) algorithm is one of the techniques for matching two point-based scans (or maps). It was presented by Besl and McKay (1992) [16].

Assuming that there are two separate scans, each of which consists of a series of points, the

scan matching process is to find a transformation best aligning one scan with the other. However, to obtain an optimized transformation, the correspondence between the two scans should be determined beforehand. Such a correspondence represents the way that the points of one scan are related to the points of the other scan. The transformation and the correspondence are therefore the two major subjects in the study of scan matching [21].

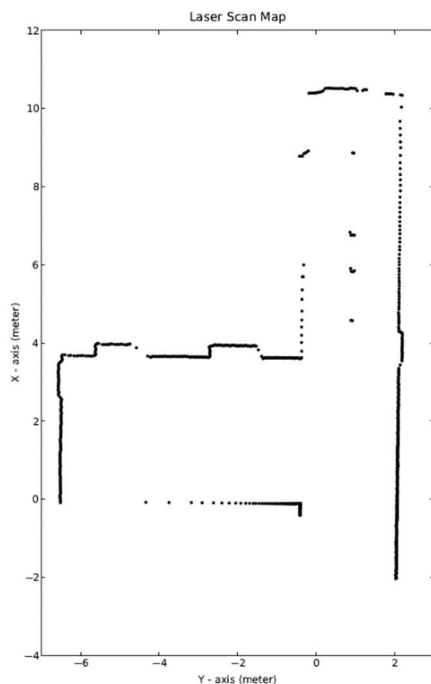


Fig. 2. A point-based map (The map consists of 1081 points. The ranging system is located at (0, 0).)



Fig. 3. The environment scanned by the ranging system for the example in Fig. 2

It often seems fairly simple to determine the correspondence between two scans by visual inspection of humans based on prior knowledge and experience regarding the general features of an environment in which the scans were taken.

However, it turns into a whole new situation for an automated system. In other words, finding the correspondence between two point-based scans is a complicated task because both of the scans consist of a set of points appearing randomly positioned. It is usually the most difficult part when conducting scan matching. Furthermore, due to a certain amount of sensing error in most cases, two sets of points from two separate scans cannot be aligned perfectly, even if the system that takes scans stays stationary. This means that real correspondence may never exist. Certain assumptions need to be made to resolve this issue. As a result, some kind of correspondence close to the truth will be defined. For the ICP algorithm that matches two sets of points, the correspondence of every point within one set is defined as its closest point within the other. Due to the fact that this assumption is often not accurate, the transformation calculated may not be accurate either. The ICP algorithm copes with this situation by alternating between determining the correspondence and estimating the transformation until the two scans are aligned closely under a specified threshold.

Given scans A and B, the following steps are to be carried out by the ICP algorithm to match (or to align) A with B:

- 1) For each of the points in A, search for its closest point in B and assign this point as its corresponding point,
- 2) Determine a transformation (i.e., a composite of a rotation and a displacement) minimizing the sum of all squared distances between pairs of points that correspond to each other,
- 3) Apply the determined transformation to A, and
- 4) Repeat steps 1 through 3 until A is closely aligned with B or some threshold is reached.

Fig. 4 shows a notional ICP process. As described in the upper left and lower left parts of the figure, the closest points are assumed to be the corresponding points although this may not be true. Despite this, it almost always brings two scans closer after each of the process iterations. More precisely, the ICP algorithm guarantees reaching one of the local minima for minimizing the sum of all squared distances between pairs of points that correspond to each other. In a few cases, such a local minimum achieved is

coincidentally global, and the two scans can be tightly matched. However, the process often falls into a local minimum that is not global and gets trapped.

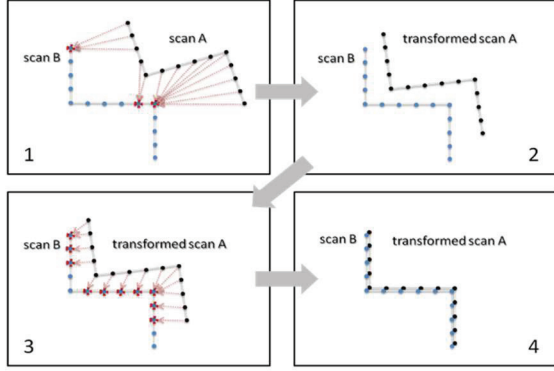


Fig. 4. An ICP process matching scan A and scan B (In subfigures 1 and 3, a search for A's corresponding points in B is conducted, while in subfigures 2 and 4, a transformation is determined and applied to A to bring it closer to B.)

As mentioned earlier, the transformation to be determined is to minimize the sum of all squared distances between pairs of points corresponding to each other. The following summarizes the algorithm for such a transformation [22].

Given two corresponding sets of points, A and B , they can be described as follows.

$$\begin{aligned} A &= \{a_1, a_2, \dots, a_n\}, \\ B &= \{b_1, b_2, \dots, b_n\}, \end{aligned} \quad (1)$$

where a_k and b_k are 3D points, and a_k corresponds with b_k for $k = 1, 2, \dots, n$.

$$\begin{aligned} a_k &= [a_{k,x} \ a_{k,y} \ a_{k,z}]^T, \\ b_k &= [b_{k,x} \ b_{k,y} \ b_{k,z}]^T. \end{aligned} \quad (2)$$

A transformation consisting of a rotation and a displacement is required to best align A with B (i.e., a_k with b_k). The terms $\bar{a}$ and $\bar{b}$ represent the centroids of A and B , respectively.

$$\bar{a} = \frac{1}{n} \sum_{k=1}^n a_k, \quad \bar{b} = \frac{1}{n} \sum_{k=1}^n b_k. \quad (3)$$

The terms A' and B' represent the sets of points obtained by referring A and B to their centroids.

$$\begin{aligned} A' &= \{(a_1 - \bar{a}), (a_2 - \bar{a}), \dots, (a_n - \bar{a})\} \\ &= \{a'_1, a'_2, \dots, a'_n\}, \\ B' &= \{(b_1 - \bar{b}), (b_2 - \bar{b}), \dots, (b_n - \bar{b})\} \\ &= \{b'_1, b'_2, \dots, b'_n\}. \end{aligned} \quad (4)$$

M is a 3×3 matrix. Its elements represent the sums of products of elements in A' and elements in B' .

$$M = \sum_{k=1}^n a'_k b'^T_k = \begin{bmatrix} S_{xx} & S_{xy} & S_{xz} \\ S_{yx} & S_{yy} & S_{yz} \\ S_{zx} & S_{zy} & S_{zz} \end{bmatrix}, \quad (5)$$

where

$$S_{xx} = \sum_{k=1}^n a'_{k,x} b'_{k,x}, \quad S_{xy} = \sum_{k=1}^n a'_{k,x} b'_{k,y}, \quad (6)$$

and so on. N represents a 4×4 real symmetric matrix. Its 16 elements are determined by the mathematical operations of the 9 elements in the 3×3 matrix M .

$N =$

$$\begin{bmatrix} (S_{xx} + S_{yy} + S_{zz}) & S_{yz} - S_{xy} & S_{xx} - S_{zz} & S_{xy} - S_{yx} \\ S_{yz} - S_{xy} & (S_{xx} - S_{yy} - S_{zz}) & S_{xy} + S_{yx} & S_{xx} + S_{zz} \\ S_{xx} - S_{zz} & S_{xy} + S_{yx} & (-S_{xx} + S_{yy} - S_{zz}) & S_{yz} + S_{zy} \\ S_{xy} - S_{yx} & S_{xx} + S_{zz} & S_{yz} + S_{zy} & (-S_{xx} - S_{yy} + S_{zz}) \end{bmatrix}. \quad (7)$$

The desired rotation represented by a unit quaternion q is the eigenvector corresponding to the most positive eigenvalue λ_{max} of the matrix N .

$$q = \text{eigenvector}(N, \lambda_{max}). \quad (8)$$

The desired displacement d is the vector from the rotated centroid of A to the centroid of B .

$$d = \bar{b} - \text{rotated_by_}q(\bar{a}). \quad (9)$$

The determined transformation (q, d) is then applied to A . Ideally, the transformed A is able to be closely aligned with B .

Fig. 5 shows a scan matching process utilizing the ICP algorithm. In this example, the process took 10 iterations to achieve the threshold. Such a threshold was defined as the improvement of decreasing the mean squared distance between pairs of points corresponding to each other in the latest iteration. Its value was set to 0.001. The process was terminated as soon as the improvement went below this value. The result shows that the two scans are closely matched.

This example was set up to reduce variability caused by some high-leverage outliers that will be defined later in this study, but not to excessively idealize the condition. The system stayed stationary when the two scans were taken. This made them similar to each other but still different because there existed the random sensing error. Furthermore, the scan in blue was rotated by 10 degrees about the origin and then translated by +1 meter and +2 meters in the x-axis and y-axis, respectively. Even though they may be aligned closely with each other, there may still be some small error in the result, which is expected. It is worth mentioning that when taking only one scan and transforming it to make up the other, the result will show that the two scans are

aligned completely without any error because there exists a perfect correspondence between them in such a specific case.

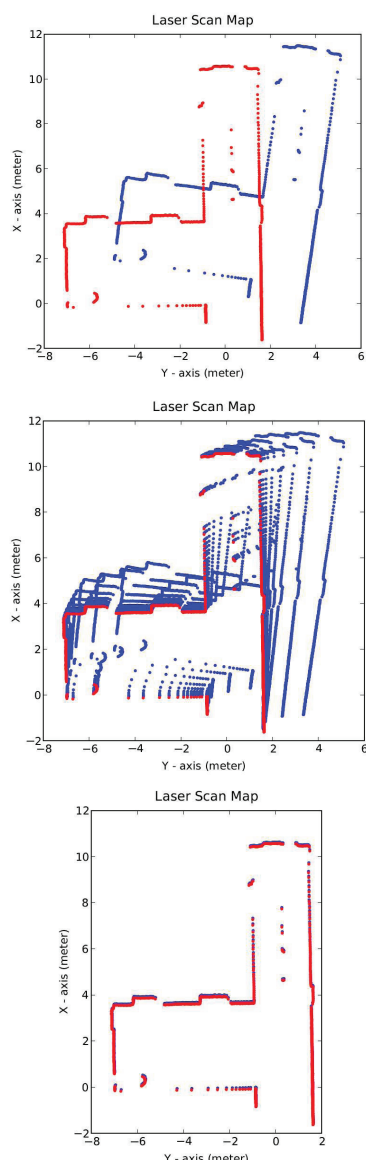


Fig. 5. A process of scan matching utilizing the ICP (The two point scans in blue and in red are shown in the upper figure. Both scans consist of 1081 points. The process iterations for converging (or aligning) the scan in blue towards the scan in red are shown in the middle figure. The result is shown in the lower figure.)

3.3 Outlier Neglecting when Using the ICP Algorithm

When matching two scans, the features (i.e. points) existing within either but having no real correspondence within the other may be regarded

as outliers. Fig. 6 illustrates the concept of outliers used in this study. In the illustration, it is assumed that the way two scans are aligned is known, although such an assumption may not always be true. It is merely intended for providing a clearer concept.

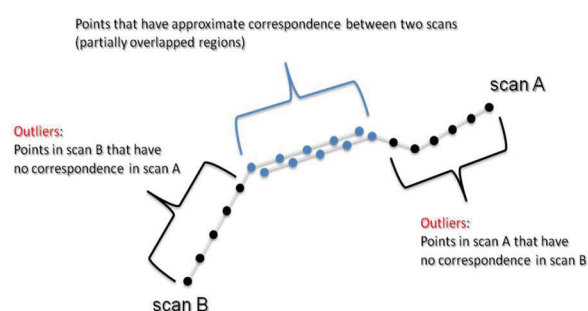


Fig. 6. The concept of outliers (The features existing within one scan but not having a real correspondence within the other may be considered to be outliers.)

Before describing the means of identifying and neglecting outliers, it is essential to realize the effect introduced by outliers and the reason to incorporate a mechanism for neglecting outliers in the process. As shown in Fig. 7, the most apparent effect introduced by outliers is that the process falls into one of the local minima.

As previously mentioned, by adopting the assumption of closest-point correspondence in each process iteration, the ICP algorithm calculates a transformation minimizing the sum of squared distances between pairs of points corresponding to each other. When the process reaches one of the local minima, any other transformation calculated in the neighborhood in the following iterations will further increase the sum of squared distances. Under this circumstance, the process is considered falling into a local minimum and being "trapped". Taking more process iterations is not useful for two scans to converge. As the example shown in Fig. 7, the long tail in the blue scan contains a large part of high-leverage outliers and will inevitably cause the local-minimum issue. The reason is that the squared distances between the points on this tail and their designated correspondence within the other scan will only get larger whenever the two scans try to converge and thus prevent the actual convergence from proceeding. This observation suggests that the issue of local minima may be resolved to some degree by neglecting a part of outliers.

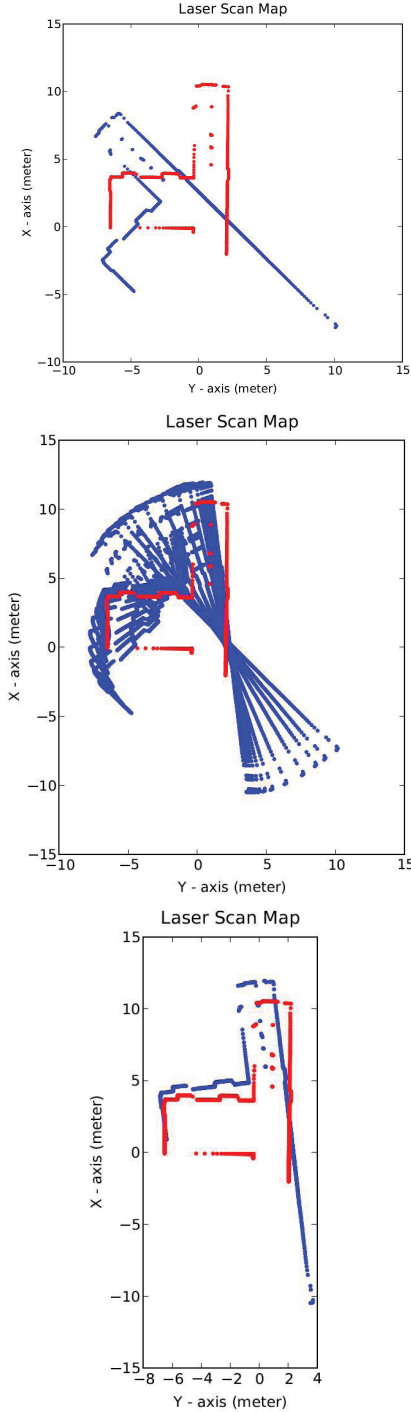


Fig. 7. ICP scan matching without neglecting outliers (Two scans are shown in the upper figure. The scans in blue and in red consist of 1047 points and 1081 points, respectively. The process iterations for the convergence are shown in the middle figure. The result is shown in the lower figure.)

Various techniques were proposed in the literature to cope with the issue caused by outliers.

For example, a measure utilizing a distance value was developed and named the fractional root mean squared distance (FRMSD) by Phillips, Liu, and Tomasi (2007) [23]. By minimizing the FRMSD between two scans, the determined transformation was reported to be less affected by outliers. This assumes that the two scans being matched are fairly similar and that a clear correspondence exists between them. Specifically, the transformation of one scan relative to the other must be small, so as to limit the part containing outliers. As the part containing outliers gets larger, some neglecting mechanism may be needed to guarantee an acceptable scan matching result.

A research study conducted by Rusinkiewicz and Levoy (2001) addressed the outlier identifying issue by justifying the distances between pairs of corresponding points [24]. Similarly, assuming that the relative transformation is small, points in one scan and their corresponding points in the other shall be within some specified distance apart. The points that are outside a specified distance from their correspondence are considered to be outliers and neglected. The same technique was initially tested in our study to approach the outlier issue. However, the effect provided is limited, and the process may eventually fall into one of the local minima and get trapped. A more tangible technique is needed to better resolve this issue.

A frustum culling approach was proposed in the studies by May, Droschel, Holz, Fuchs, and Nuchter (2009) [25] and by Holz and Behnke (2010) [26]. The term, frustum, represents the field of view from a certain perspective. The points outside the specified frustum are considered to be outliers and neglected.

By adopting an approach similar to frustum culling, the mechanism for identifying and neglecting outliers developed in our study specifies the angular range of the scan being aligned with from the ranging system's perspective as the frustum. As shown in Fig. 8, when the process is to converge scan A towards scan B, the part of A falling outside of the angular range of B will be considered to be the part consisting of outliers. This part will be identified and neglected in every ICP iteration before assigning the correspondence. To better illustrate the concept of the identifying mechanism, the figure is showing the final stage of scan matching

(i.e. the last iteration of the process) at which the two scans being matched almost converge and the majority of outliers are able to be identified and neglected. On the other hand, at the beginning stage, since the two scans have not converged, the process will only identify a small part of the outliers. As it proceeds, the outliers identified will increase incrementally. Also, outlier neglecting is only used to find the correspondence and to calculate the optimized transformation in every ICP iteration. None of the points is actually removed. The transformation will be utilized to transform all of the points in the original scan.

Fig. 9 shows the result of the ICP process integrated with the outlier neglecting mechanism for the same scans shown in Fig. 7. By this means, the two scans are closely matched with each other.

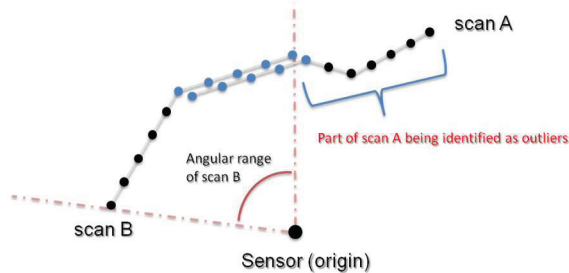


Fig. 8. Notional illustration of the part of a scan being identified as outliers (The part of scan A falling outside of the angular range of scan B from the sensor's perspective will be identified as outliers and neglected. The sensor (origin) point is the ranging system's location.)

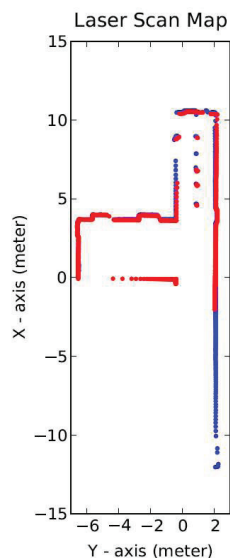


Fig. 9. The result of the ICP process integrated with the outlier neglecting mechanism

3.4 Mergence of the Matched Point Scans

Localization and mapping conducted in this study is characterized by a process of scan matching that converges the old scan towards a scan that is newly acquired. The old scan represents either one single scan or the combination of a sequence of scans taken so far.

After completing scan matching, a certain process needs to be carried out for merging the two separate scans being matched into a single one. The process for mergence will depend on the requirements specified, such as the nature of the implementation (i.e., post or real-time processing), and the map's intended use.

Since there usually exists a fairly large overlapped region between any two scans being matched in a consecutive process of scanning, to keep all points of two scans after merging them into one single scan may not be efficient. The number of redundant points will keep growing and thus will reduce the efficiency of the subsequent process of scan matching considerably. This situation will prevent the process from being conducted in real time. A method characterized by the concept of sparse point maps was proposed to resolve this issue [26]. Its purpose is to avoid storing duplicate points by carrying out one additional search of correspondence and rejecting those points of one scan with corresponding points identical to themselves existing within the other scan. An issue associated with this method is that the time consumption for the additional search of correspondence may considerably slow down the process since it is applied to all of the points within the scan, not merely a down-sampled subset as frequently adopted in every ICP iteration. (It is noted that the time consumption of each ICP iteration can be effectively reduced by down-sampling the scan points for correspondence searches.)

For our study, the method for mergence consists of the following steps. Fig. 10 illustrates such a merging process.

- 1) Keep all points in the new scan. The newer scan is intuitively more accurate in comparison with the older one that contains a relatively larger accumulated error.
- 2) Discard those old scan points lying inside of the overlapped region of the two

matched scans (i.e., within the new scan's angular range). This removes a part of old and duplicate information to avoid unlimited data growth.

- 3) Following the previous step, keep those points lying outside of the overlapped region of the two matched scans.

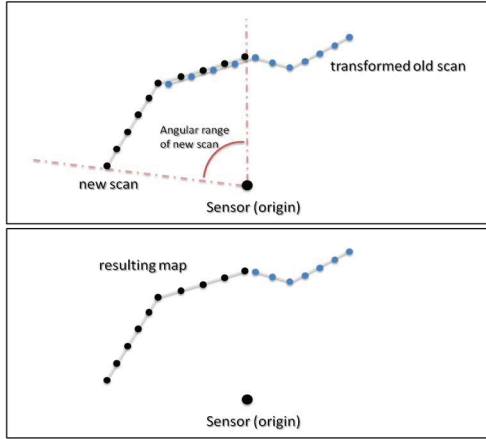


Fig. 10. Notional illustration for the process of mergence (The upper figure shows two matched point scans to be merged. The lower figure shows the result.)

3.5 Real-time Localization and Mapping

The incremental process for localization and mapping begins with one scan taken by the ranging system at a certain location. Such a scan is considered to be the original old scan. Note that a scan taken earlier or a known map constructed by matching multiple scans beforehand may also be used, on the condition that it adopts a representation the same as the one used in the process. For every newly acquired scan, the process cycle conducts the following two tasks:

- 1) The ICP scan matching process aligning the old scan with the new one. (The process includes the outlier neglecting mechanism.)
- 2) The merging process combining the two scans being matched into one. (The resulting scan is in turn regarded as the updated old scan.)

The transformation used to align the old scan with the new one is calculated during each scan matching process cycle. Such a transformation at the end of the k th cycle consists of a rotation q_k described by a unit quaternion and a displacement d_k described by a 3-dimensional (3D) vector. The system's orientation Q_k and position D_k relative

to the initial values, Q_0 and D_0 , after completing the k th process cycle are determined in the following equations.

$$\begin{aligned} Q_k &= q_k^* Q_{k-1}, \\ D_k &= Q_k(-d_k)Q_k^* + D_{k-1}. \end{aligned} \quad (10)$$

The orientation Q_k is represented by a unit quaternion, while the position D_k is represented by a 3D vector. The superscript $*$ indicates the complex conjugate of the quaternion, and the subscript k indicates the k th cycle of the process. Quaternion multiplication is the operation used in the equations. The initial orientation Q_0 and position D_0 are as the following.

$$\begin{aligned} Q_0 &= [1.0, 0.0, 0.0, 0.0], \\ D_0 &= (0.0, 0.0, 0.0). \end{aligned} \quad (11)$$

The absolute initial values of orientation and position can be adopted instead. In such a case, Q_k and D_k will be represented by the absolute values as well.

A general concept of real-time processing often indicates that the algorithm is able to process inputs (e.g., sensor data) as soon as they are present without requiring any buffering mechanism. For every process cycle, the presented process in our study takes one new scan over the environment and matches (and also merges) the older one built from the previous cycle with the new one just acquired. It is considered to be a real-time process if it can be conducted continuously as the ranging system moves. A speed as slow as humans' natural walking speed may be set for the system. Therefore, it is acceptable for allowing the real-time process to take 1 to 2 seconds on average to complete each process cycle. Note that the time for taking a new scan (which is reported to be in tens of milliseconds) is trivial and negligible in comparison to the time for matching and merging scans.

For real-time localization and mapping, efficiency is a major issue to be coped with. Specifically, the time required for every process cycle must be reduced so that it is able to operate reasonably fast in real time. The most time-consuming operation during a process cycle is the search for correspondence between two scans in each ICP iteration.

When adopting a brute-force approach, the correspondence search for each closest point is completed by calculating and comparing all squared distances between all points of the new scan and each point of the old scan. Therefore,

assuming the numbers of points in the old and new scans are M and N , respectively, such a search in each ICP iteration of each process cycle has a complexity of $O(MN)$, which is computationally expensive.

To resolve the complexity issue, Maneewongvatana and Mount (1999) proposed an approach that utilizes a tree-search technique (named the K-D tree) [27]. By incorporating this method, conducting a search among a series of points for the closest one is more efficient. The concept of the K-D tree is to build a binary tree for the data points. Each node of the tree defines one axis and divides the points along this axis according to their coordinates. In this way, for every new scan acquired, the structure of a K-D tree is constructed. In each ICP iteration, the closest point to each point in the old scan will be searched within this K-D tree. The complexity for such a search is $O(\log_2 N)$ if there are N points in the new scan. For the complete correspondence search with M points in the old scan, the complexity will be $O(M \log_2 N)$, which is less complex and more efficient than the brute-force approach. Note that building a K-D tree has a complexity of $O(N \log_2 N)$. During each process cycle, the K-D tree structure is only built once.

Although there is an improvement in efficiency gained by utilizing the K-D tree search method, completing each process cycle may still be too time-consuming, especially when the two scans being matched are large in size (i.e., containing large numbers of points). Certain means may be needed to ease the computational load on the search for correspondence. Our study adopts an approach that down-samples the old scan by a specified number. Such down-sampling is applied at the start in each of the ICP iterations to decrease the number of old scan points partaking in search for correspondence. The process efficiency may be improved to a degree. However, it may also be possible to affect accuracy if the sampled point features are not sufficient to offer enough information for the process. This is one situation in which an accuracy-efficiency trade-off needs to be determined.

An example of one localization and mapping process cycle is shown in Fig. 11. In such an example, a comparison of the time consumption of the process using different correspondence search methods and different ICP setups is shown

in Table 1. It is noted that the process is more efficient by applying down-sampling and incorporating the K-D tree search method so that it can be conducted in real time. Although specifying a larger value for the threshold can reduce the processing time as well, this usually decreases the accuracy directly and is not emphasized in our study.

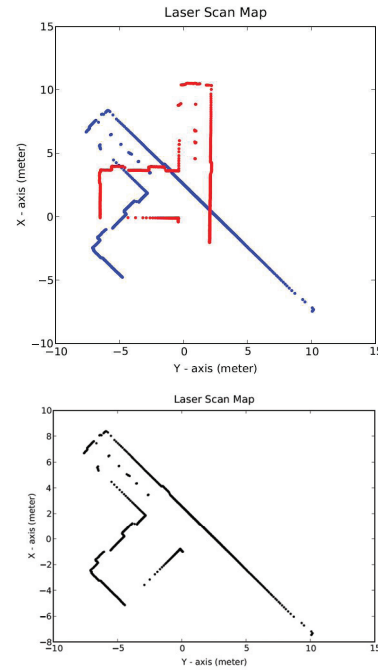


Fig. 11. An example of one localization and mapping process cycle (Two separate scans are shown in the upper figure. The scans in red and blue are the old and new ones consisting of 1081 points and 1047 points, respectively. The resulting scan consisting of 1242 points is shown in the lower figure.)

Table 1. Comparison of time consumption

Methods Incorporated	Time (seconds)	# Iterations
Brute-force	127.49573576200	19
K-D tree	10.70492927460	19
Down-sampling by 20 + K-D tree	1.13340847026	20

Threshold (meters²):

Reduction in the mean squared distance ≤ 0.000025

This table shows the comparison in process time when applying different correspondence search methods and different ICP setups (for the same example in Fig. 11). The program was executed on a computer equipped with an Intel Core i7 2.20 GHz processor. It was implemented by the Python scripting language and was not optimized. The result is only for an approximate comparison.

Fig. 12 shows a process of real-time point-based localization and mapping that adopts the improved ICP algorithm (i.e., the ICP algorithm integrated with the outlier neglecting mechanism).

In this example, the ranging system alternated between moving straight forward and making a left turn until arriving at its initial location (i.e., moved approximately in a rectangular loop). The point set in blue describes the map, while the one in red represents the system's trajectory. The map was constructed consecutively by matching and merging scans taken during the movements of the system. The system's coordinates are represented in the north-east-down (NED) coordinates relative to its initial position and orientation. For our specific case, a 2D map is represented. Only the north and east coordinates (i.e., the x and y axes) are adopted. Fig. 13 shows an image of the real environment taken from the relative location at the lower-right corner on the map. As observed in Fig. 12, it may not be easy to identify the error of the estimated transformation by examining the final map. Alternatively, it may be reflected in the trajectory being estimated. Although the real initial and final locations were perfectly the same, the estimated values may still show a large difference in between. This is caused by the error accumulated in every scan matching process cycle. The distance error of the estimated final location from the real one is approximately 1.45 meters, which gives a mean distance error of 0.02 meters per scan-matching process cycle (for a total number of 80 process cycles matching 81 scans). Certain means may be needed to effectively reduce such an error to some degree.

IV. IMPROVED ICP ALGORITHM COMBINED WITH A FEATURE-BASED ALIGNMENT CORRECTION ALGORITHM

In this section, a feature-based alignment correction algorithm is presented to resolve the issue of accumulated errors associated with localization and mapping using the ICP algorithm.

4.1 Line-based Description for Point Maps

The point-based representation is sufficient for describing the outlines of general environments. However, to cope with the accumulated error, some other representation will be worth investigating in a sense that it may offer better features for correcting the alignment error.

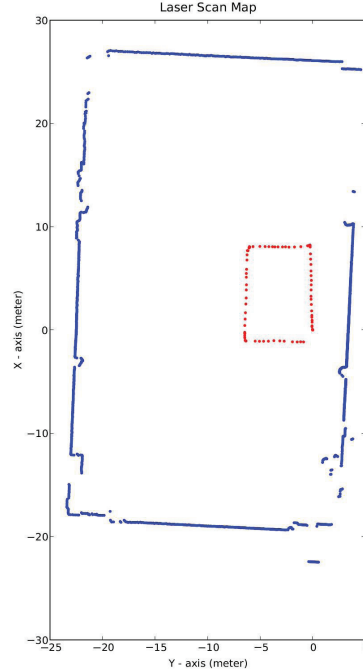


Fig. 12. A process of real-time point-based localization and mapping (The point set in blue represents the map, while the one in red shows the trajectory. The map was constructed by incrementally matching and merging 81 scans. It consists of 1473 points. The coordinates are relative to the system's initial position and orientation. The real initial and final positions are both (0,0). The estimated ones are (0,0) and $(-1.15098078202, -0.874567350456)$, respectively.)



Fig. 13. The actual environment for the process shown in Fig. 12

The representation utilizing line segments is adopted for the following reasons:

- 1) The outline of a general environment can usually be illustrated by a series of 2D line segments from the top view.
- 2) Line segments describe the boundaries (e.g., obstacles and walls) better than points. In a point map, it is often difficult

- to tell whether the space is occupied or not between any two adjacent points.
- 3) Using line segments is more computationally efficient since every single line segment can represent all points on it.
 - 4) When conducting ICP scan matching, instead of adopting all points in the original point scan for the correspondence search, utilizing the start and end points on the line segments may be more efficient, since it systematically down-samples the original scan.
 - 5) An algorithm analyzing line features may be used to correct the alignment error after each ICP localization and mapping process cycle.

Hough transform is one technique utilizing line features [28]. As illustrated in Fig. 14, one straight line in the 2D coordinates is described by the following equation.

$$y = mx + b, \quad (12)$$

m and b are the slope and intercept parameters, respectively. Therefore, the line can be represented by (m, b) . One issue associated with this representation is its instability. When the line gets vertical (or horizontal), the value of m (or b) becomes infinite.

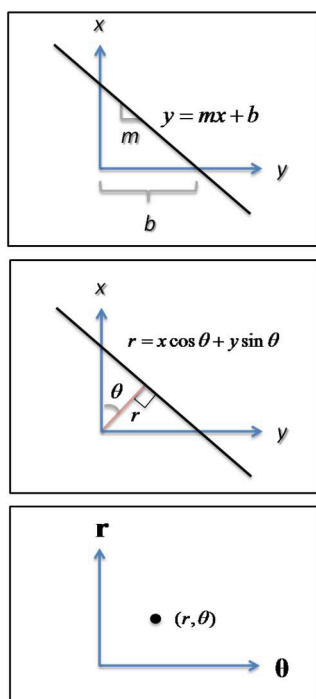


Fig. 14. One straight line represented in the Cartesian coordinates (upper and middle) and the r - θ coordinates (lower)

The same line may be defined by utilizing the range r and bearing θ as well. The range r represents the distance of the line from the origin, and the bearing θ represents the angle of the vector from the origin to the closest point of the line.

$$r = x \cos \theta + y \sin \theta. \quad (13)$$

Given two points (x_1, y_1) and (x_2, y_2) on a straight line, θ and r can be calculated as follows [29].

$$\theta = \begin{cases} \tan^{-1} \left(\frac{(x_2 - x_1)}{(y_1 - y_2)} \right), & \text{if } y_1 \neq y_2. \\ \pi/2, & \text{if } y_1 = y_2. \end{cases} \quad (14)$$

$$\begin{aligned} r &= x_1 \cos \theta + y_1 \sin \theta \\ &= x_2 \cos \theta + y_2 \sin \theta. \end{aligned} \quad (15)$$

The line is therefore described by one particular point in the r - θ coordinates by performing the Hough transform. A useful concept is that if the distances between multiple points in the r - θ coordinates are short enough, these points can be represented approximately by one single line in the x - y coordinates.

Given a point map, the procedure to convert it into a line map is described in the following steps. (Fig. 15 shows a notional illustration of such a conversion.)

- 1) Connect every two adjacent points by one line segment if the distance between them is short enough to form a part of the boundary. A threshold value for the distance needs to be specified. Each line segment has 5 features: the start point, the end point, the bearing θ , the range r , and the length.
- 2) Examine every two adjacent line segments to decide if the two points representing them in the r - θ coordinates are close enough for them to be combined, and keep a record of these combined points. A threshold value for the distance needs to be specified. Any cluster of points with distances in between shorter than the distance threshold in the r - θ coordinates represents one group of line segments being approximated by a single one.
- 3) For each group of line segments being combined and approximated by one single line segment, extract all of the points originally associated with these segments and determine a segment of the

least square line fitting those points. All of such line segments being determined are to take the place of the original line segments for describing the line map.

Fig. 16 shows the result of a conversion process from points into line segments. The number of line segments and their lengths in the result may depend on the value of the threshold specified for combining the original shorter line segments. In our study, the threshold value represents the upper bound distance between points in the r - θ coordinates. It was set to 1.0 for this example. Distances between multiple points below this threshold will be regarded short enough for these points to be approximated by a single one. These points will also be represented by one single line in the x - y coordinates. Intuitively, adopting line segments to describe the map is expected to reduce the required space for maintaining it, since a large number of points in the original map are to be replaced by fewer line segments.

4.2 Scan Matching for Aligning a Line Map Towards a Point Map

The line-based localization and mapping process is to estimate the transformation and to incrementally build a line map simultaneously in the meantime of conducting scan matching. Since every new scan just acquired is still in the form of a point map, it will be straightforward to match the maintained line map with the new one that is a point map.

A line map consisting of line segments may be directly decomposed into points by drawing out the start point and the end point from every line segment. Therefore, the ICP algorithm may still apply to aligning a line map towards a point map. In this way, the process will be more efficient than originally to match two point maps because the number of points is significantly reduced. For aligning a line map towards a point map, here are several steps to follow:

- 1) Draw out the start point and the end point from every line segment in the line map to form a group of points.
- 2) Align the group of points with the point map by utilizing the improved ICP algorithm discussed in this study.
- 3) Apply the calculated transformation to the line map.

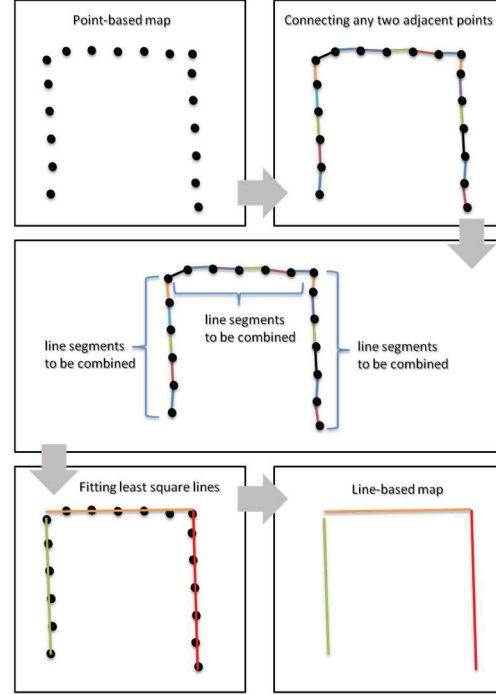


Fig. 15. A notional illustration of the conversion from a point map to a line map

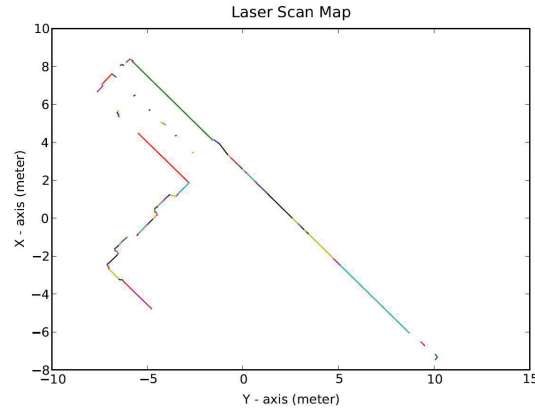


Fig. 16. The result of a conversion process from points into line segments (The original point map consists of 1047 points. The resulting line map consists of 175 line segments.)

Fig. 17 shows a process example that aligns a line map towards a point map. Adopting the same sensor measurements, Table 2 shows a comparison of time consumed when conducting scan matching for different types of maps. One case was aligning between point maps, and the other case was aligning a line map towards a point map. In either case, the process was conducted without down-sampling the points in the map beforehand for each search of correspondence. It is observed that conducting the alignment of a

line map towards a point map achieved greater efficiency. To process in real time, the consumed time for either case may be reduced further by appropriately conducting down-sampling for the search of correspondence in every ICP iteration.

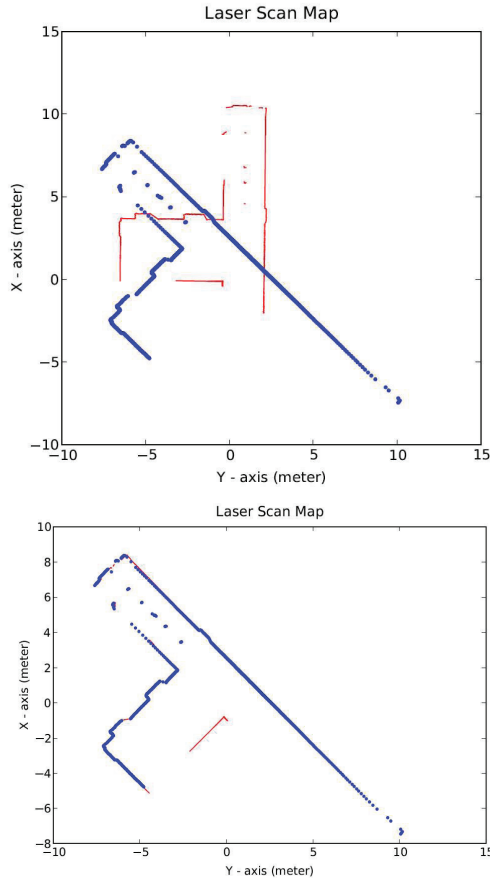


Fig. 17. A process example showing the alignment of a line map towards a newly acquired point map (The point map consists of 1047 points. It is illustrated in blue. The line map consists of 316 line segments and is illustrated in red. The initial two separate maps are shown in the upper figure. The result is shown in the lower figure.)

Table 2. Comparison of time consumption

Types of Maps	Time (seconds)	# Iterations
point map / point map	10.7217815053	19
line map / point map	7.81693578522	23
Threshold (meters²): Reduction in the mean squared distance ≤ 0.000025		

This is a comparison of processing time consumption between aligning a point map and a line map towards a point map respectively. Both were conducted without down-sampling the points beforehand for the search of correspondence. The raw measurements are the same as used in Fig. 17. The program was executed on a computer equipped with an Intel Core i7 2.20 GHz processor. It was implemented by the Python scripting language and was not optimized. The result is only for an approximate comparison.

4.3 The Line Feature-based Alignment Correction Algorithm

The issue associated with the point-based process of localization and mapping is the cumulative estimation error. Such an issue still exists for the line-based process because the same technique (i.e., the ICP) is adopted. It is observed that by adjusting the threshold value for taking more iterations, the scan matching accuracy may be enhanced to some degree. However, more iterations may require more processing time but only offer a limited improvement. Some other measures still need to be investigated.

An algorithm utilizing line features (e.g., the range r and the bearing θ) is presented in this study to adjust the alignment between two line maps.

Assuming that two line segments A and B (as shown in Fig. 18) are corresponding to each other, to align the straight line extending A towards that extending B , complete the following two steps:

- 1) Rotate A by an angle of $(\theta_2 - \theta_1)$ about the origin.
- 2) Translate A by (x_0, y_0) , where

$$\begin{aligned} x_0 &= (r_2 - r_1) \cos \theta_2, \\ y_0 &= (r_2 - r_1) \sin \theta_2. \end{aligned} \quad (16)$$

The unit quaternion for performing the rotation is calculated by

$$q(\theta_2 - \theta_1) = \left[\cos\left(\frac{(\theta_2 - \theta_1)}{2}\right), 0, 0, \sin\left(\frac{(\theta_2 - \theta_1)}{2}\right) \right]. \quad (17)$$

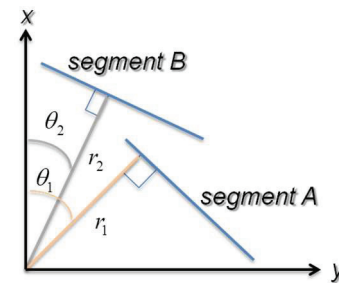


Fig. 18. Two line segments corresponding to each other in the x - y coordinates

To fix the error in the alignment between two maps (or scans), the line feature-based alignment correction algorithm aligns a pair of corresponding line segments, each of which is extracted from each of the two maps (or scans). For better convergence, such a process may be conducted several times by adopting different pairs of corresponding line segments that are not

in parallel with the pairs already used. This is assuming that the pair of line segments corresponding to each other in the two scans are able to be determined. However, correctly determining the correspondence may not be a simple task, and any incorrect determination will only increase the error of aligning two scans. Therefore, the correction algorithm was developed as an extension based on the ICP algorithm. When the two scans being matched are nearly aligned with each other after completing the iterations of ICP, the pairs of corresponding line segments are to be extracted by comparing the line features of the segments in the two scans (e.g., lengths, ranges, bearings, and positions of mid-points).

The determination of pairs of corresponding line segments between two line scans (e.g., X and Y) accomplished by the line feature-based alignment correction algorithm is to complete the following steps:

- 1) Select the longest 10 line segments in X .
- 2) For each of the 10 segments in X , select the one in Y with the smallest difference in length as its correspondence.
- 3) Verify each of the 10 pairs of corresponding line segments by checking if the conditions as follows are satisfied.
 - 3.1) The lengths of the two segments are both greater than 2 (meters).
 - 3.2) The difference in length is less than 1 (meter).
 - 3.3) The difference in range (i.e., the difference between r_1 and r_2 in Fig. 18) is less than 1 (meter).
 - 3.4) The difference in bearing (i.e., the difference between θ_1 and θ_2 in Fig. 18) is less than 0.4 (radians).
 - 3.5) The mid-point distance between the two segments is less than 0.5 (meters).

It may also be possible that none of the line segments corresponding to each other is determined in some cases. The specified number of segments being selected and the values of thresholds are adjustable for satisfying the requirements in different conditions. The values in this study are solely adopted to examine the feasibility of the algorithm and are not necessarily optimal.

An example of incorporating the algorithm

is shown in Fig. 19. The results before and after applying the algorithm are shown in the upper and lower figures, respectively. One corresponding pair between the two maps is determined. A small error in the alignment between the two maps (in red and in blue) in the upper figure is corrected as shown in the lower figure. Note that before such a correction is made, the point map must be converted into a line map beforehand. The alignment of a line map towards a point map rather than towards a converted line map in the lower figure is meant for providing a better comparison to that in the upper figure.

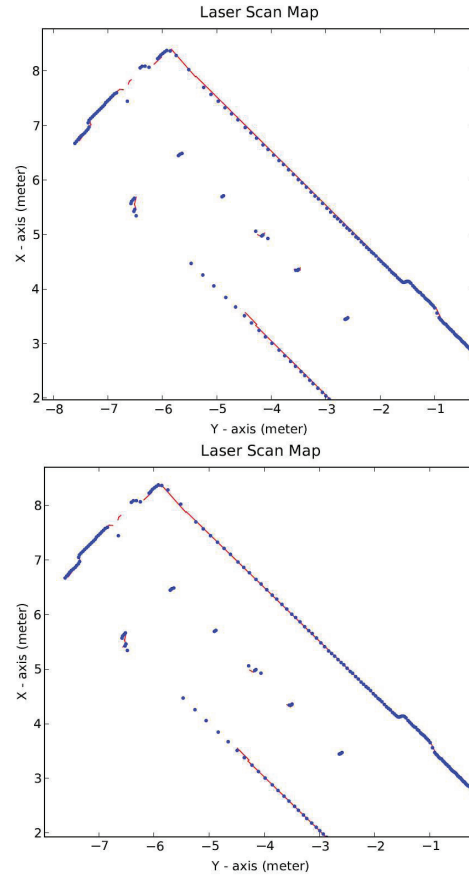


Fig. 19. An example of integrating the improved ICP algorithm with the alignment correction algorithm using line features (The results before and after incorporating the alignment correction algorithm are shown in the upper and lower figures, respectively.)

4.4 Real-time Processing

The process starts with the first point scan acquired. Such a scan is transformed into a line scan and considered to be the initial old scan. It is worth mentioning that a previously constructed

map is also acceptable, on the condition that such a map is able to be described by or transformed into a series of line segments. For each subsequently acquired new point scan, the following steps are carried out by the process cycle.

- 1) Align the old line scan towards the most recently acquired new point scan by utilizing the improved ICP algorithm proposed in this study.
- 2) Convert the point scan into a series of line segments (i.e., a line scan).
- 3) If the corresponding line segments between the old line scan and the new line scan are able to be determined, apply the line feature-based alignment correction algorithm to correct the error in the alignment between the two scans.
- 4) Merge the two closely aligned line scans into one by adopting the same concept of merging two point scans discussed in Section 3. The resulting scan is considered to be the newer representation of the old scan for the subsequent process cycle.

Fig. 20 illustrates the result of a post-processed experiment of line-based localization and mapping. It was intended for comparing the performance of the line-based process in estimation accuracy with that of the point-based process illustrated in Fig. 12. The same raw sensor data was fed to the line-based process. The overall distance error between the estimated final position and the real one is approximately 0.63 meters, which gives a mean distance error of 0.01 meters per scan-matching process cycle (for a total number of 80 process cycles matching 81 scans). Judging from the shorter distance error, it is evident that the line-based process that incorporates the line feature-based alignment correction algorithm with the improved ICP algorithm performs better since the accumulated estimation error is reduced.

The result of a real-time process of line-based localization and mapping is illustrated in Fig. 21. An infrared precision position tracker (PPT) [30] was utilized to measure the position of the system concurrently throughout the experiment to verify the estimation accuracy of the process. The overall root mean square (RMS) error in the PPT measurements was reported to be in centimeters (that is 6.68 cm, to be exact),

which is sufficiently small for considering such measurements to act as the ground truth. Fig. 22 shows such an experiment comparing the trajectories obtained by the process proposed in this study and the PPT. The comparison verifies the estimation accuracy of the proposed process since the trajectories coincide closely. The RMS error of the trajectory estimated by conducting the proposed process is approximately 0.07 (meters) with respect to the one measured by the PPT. It is worth mentioning that the moments in time at which the sensor data were collected for both techniques were different because they were processed independently. For this reason, the two sets of data points describing the two trajectories will never sit exactly on top of each other.

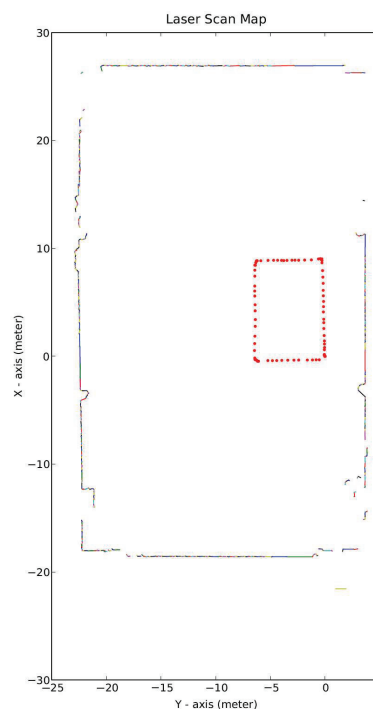


Fig. 20. A process of line-based localization and mapping that incorporates the line feature-based alignment correction algorithm with the improved ICP algorithm (The group of colored line segments illustrating the outline of the surrounding environment represents the map, and the sequence of red points describes the trajectory of the system that takes scans. The map was constructed by aligning and merging 81 individual scans. It consists of 648 line segments. The real initial position and final position are both (0,0), while the estimated ones are (0,0) and $(-0.327111495504, -0.533314961374)$, respectively.)

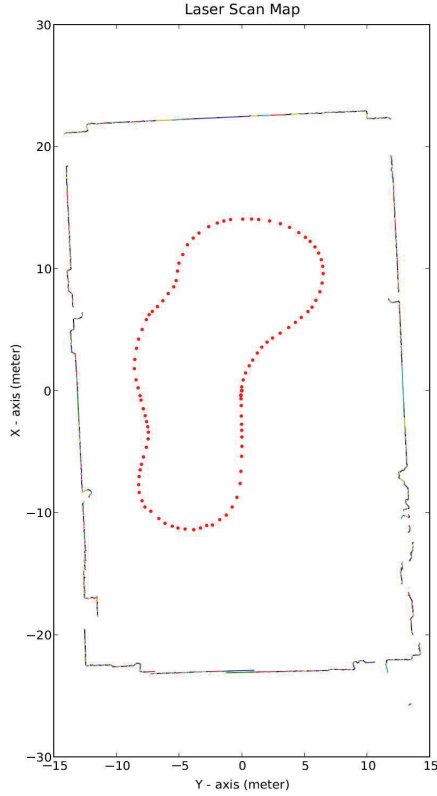


Fig. 21. A real-time process of line-based localization and mapping that incorporates the line feature-based alignment correction algorithm with the improved ICP algorithm (The group of colored line segments represents the map, and the points in red describe the trajectory of the system. The map was constructed by aligning and merging 106 individual scans and consists of 846 line segments. The real initial position and final position are both at (0,0). The estimated ones are at (0,0) and $(-0.348965542645, -0.071385533758)$, respectively.)

V. LOCAL MINIMUM AVOIDANCE MECHANISM

The ICP algorithm guarantees a local minimum for aligning one scan towards the other. Most of the time, such a local minimum is also the global minimum. It is observed that neglecting a part of outliers may resolve the local minimum issue to some degree. However, such an issue may occasionally occur even when the outlier neglecting mechanism is applied. As illustrated in Fig. 23, when the process has fallen into one of the local minima, the two scans will never converge regardless of how many iterations are conducted.

Various techniques approaching the problem of optimization (i.e., either minimization or maximization) have been proposed in the literature. Most of the studies face a similar issue, the local optimum. For example, one of the greedy-based algorithms, the hill-climbing search, is a technique for mathematical optimization [31]. It starts with an arbitrary solution and tries to find a better one iteratively by applying a small modification to its solution incrementally. The ICP algorithm can be classified as a greedy-based algorithm. This type of algorithm is fairly efficient and always guarantees to reach one of the local optima. Simulated annealing (SA) is another technique searching for optimization [32]. The insight into this problem was gained from the process of annealing in metallurgy. It is intended for determining an adequate approximation to the global optimum in a specified amount of time. Such a technique provides the process with a means to escaping a local optimum by allowing some solutions not better than the current one. The probability of allowing these solutions is gradually decreased as the process moves towards the finish time.

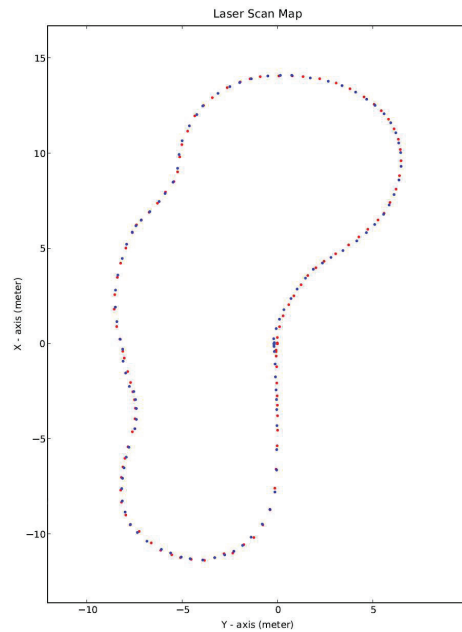


Fig. 22. An experiment comparing the trajectories obtained by the process proposed in this study (in red) and the infrared precision position tracker (PPT) (in blue) (The RMS error of the trajectory estimated by the proposed process is approximately 0.07 (meters) with respect to the one by the PPT.)

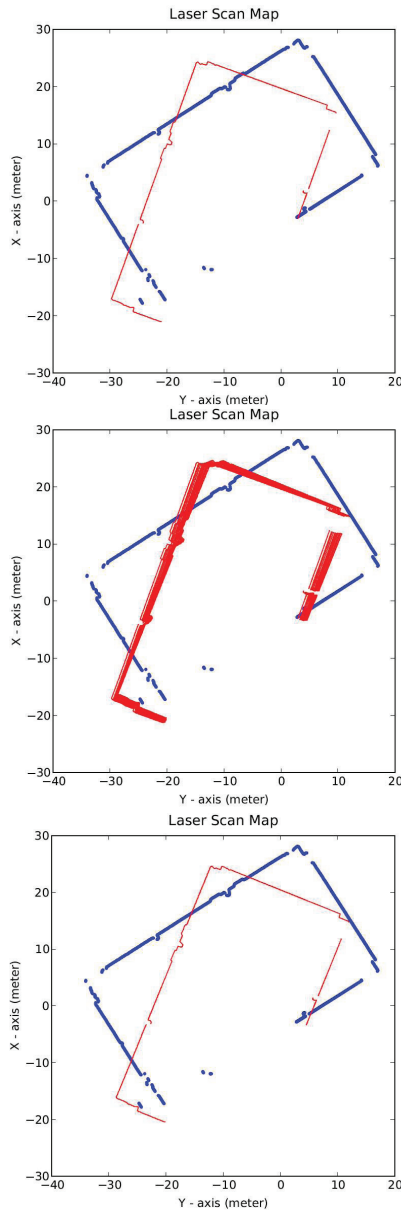


Fig. 23. An ICP process that has fallen into a local minimum (Two individual scans are shown in the upper figure. The process iterations for the convergence of the line scan towards the point scan are shown in the middle figure. The result is shown in the lower figure.)

The greedy-based algorithm may also be able to escape local optima by some means. Generally, there are two approaches:

- 1) Restarting the process with a random initial condition.
- 2) Applying a random amount of sideways move.

Both approaches are suitable for being incorporated into the ICP process. A user-

specified or random rotation that serves as the integration of the two approaches can be used to avoid the currently encountered local minimum. The local minimum avoidance mechanism proposed in this study completes the following steps:

- 1) Carry out the iterations of the ICP scan-matching process until reaching the threshold.
- 2) Examine the mean distance between pairs of corresponding points to distinguish whether the process has fallen into one of the local minima.
- 3) If the process has fallen into one of the local minima, apply a user-specified or random rotation to the scan to be aligned towards the other one. Its direction may be kept the same as that in the previous process iteration.
- 4) Re-conduct the ICP iterations until reaching the threshold.

Fig. 24 shows the result of the process incorporating the mechanism for aligning the same scans in Fig. 23.

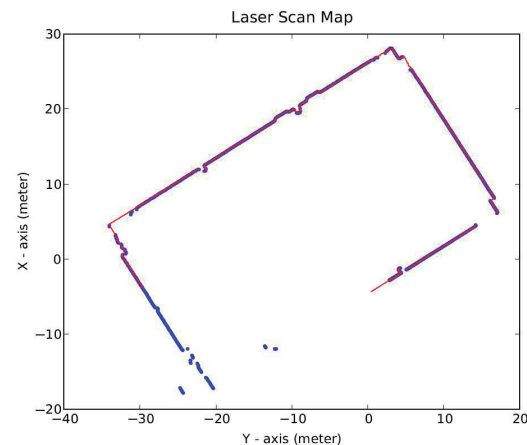


Fig. 24. The result of the ICP process incorporating the local minimum avoidance mechanism

VI. CONCLUSION

This study presented a real-time ranging sensor-based localization and mapping algorithm that combines an improved ICP algorithm, an alignment correction algorithm using line features, and a mechanism avoiding local minima. It began with an examination of the point-based process using the ICP algorithm. One of the main issues associated with the ICP algorithm is that the process may get trapped in a local minimum.

Such an issue is often caused by outliers. To resolve this, a mechanism neglecting a part of outliers with high leverage was incorporated in each process iteration. For processing in real time, a down-sampling mechanism and a tree-search technique were incorporated for the search of correspondence to reduce processing time.

Although the point-based localization and mapping process produces acceptable results, there still exist issues associated with efficiency and accuracy that must be coped with. A line-based description for maps was adopted to reduce processing time, and an alignment correction algorithm using line features was built to correct the error in the alignment between two scans. The proposed line-based process produces better results than the original process.

Although the issue due to local minima may be resolved to some degree by neglecting a part of high-leverage outliers, it may still occur occasionally. To further resolve such an issue, a local minimum avoidance mechanism was incorporated.

6.1 Contributions

The major contribution presented by this study is the development of a real-time ranging sensor-based localization and mapping algorithm that includes:

- 1) an improved ICP algorithm,
- 2) a line-feature based alignment correction algorithm for reducing the scan matching error, and
- 3) a local minimum avoidance mechanism for coping with the local minimum situations so as to improve the scan matching result.

6.2 Limitations

The ranging sensor-based localization and mapping algorithm is based on the following assumptions and conditions:

- 1) Sufficient overlap between every two consecutive scans is necessary to guarantee successful scan matching. This makes certain that enough information of correspondence between them can be provided. In other words, the transformation in between is assumed small. For instance, a rotation less than 45

degrees and a displacement less than 10 meters in magnitude are recommended.

- 2) Partly following the previous assumption, the velocity is required to be as slow as the natural walking speed of humans for keeping the transformation relatively small. Besides, some duration of time is taken to measure the distances counterclockwise from its environment. Measuring (i.e., scanning) during system movements may skew the resulting scan. It is recommended to keep the velocity slow to reduce the effect of skewness.
- 3) The maximum dimensions of environments suitable for this algorithm depend on the effective sensing range of the sensor system. Proper sensor devices need to be adopted for different conditions. For example, in an open space with its boundaries far beyond the maximum sensing range, there may be little or no correspondence between scans. Such an environment is not suitable for utilizing this algorithm.

6.3 Considerations for Future Works

The ranging sensor-based localization and mapping algorithm is expected to be capable of coping with 3D environmental models since the data representation and the mathematical operations are all 3-dimensional. However, a 2D laser ranging sensor was adopted in this study. A major consideration for such adoption is that 2D sensor units are generally significantly less expensive (both financially and computationally) than 3D units. For future development, the adoption of 3D sensors and the applications on 3D models may also be taken into consideration.

Future studies may also focus on refining the localization and mapping algorithm by investigating different sensing techniques and determining the optimal representations and scan matching algorithms that complement the adopted techniques.

A further consideration for future work may be to quantitatively compare the performance of different approaches (e.g., different algorithms, sensing techniques, etc.) and to determine the preferred approaches for different conditions of environments.

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