ONLINE CELL DECOMPOSITION WITH A LASER RANGE FINDER FOR COVERAGE PATH IN AN UNKNOWN WORKSPACE

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Abstract- Although autonomous mobile robots have been increasingly popular in a known workspace, but they face the challenging task of operation in an unknown workspace. This paper presents a sensor-based image matching for online cell decomposition to plan coverage path-that provides a mobile robot one of suitable complete coverage of an unknown rectilinear workspace. Authors develop a new method for cell decomposition that is called adaptive cell decomposition based on two assumptions. First, cells are composed by adaptive cell decomposition method from explored map. Second, virtual edges can be used to compose cells in this method. The basis of this approach is same as that of the boustrophedon cell decomposition. The proposed algorithm supports online coverage for a robot to explore unknown workspace and to achieve adaptive cell decomposition simultaneously in order to cover the workspace.

Keywords- Cell Decomposition, Online Decomposition, Coverage Path, Iterative Closest Point

I. INTRODUCTION

Simultaneous localization and mapping (SLAM) and online path planning (OPP) are main issues of the autonomous mobile robots in an unknown and real environment, because a robot is not capable of performing a task such as autonomous navigation without any information about its own pose and the surrounding workspace. For this problem, a robot must know its position at each time step and build a reasonable map of workspace which gives strong support for navigation of the robot. Navigation system of a robot integrates many techniques such as localization and map building and coverage path planning of the target region in order to maximize its performance. One of the most important obligate performances of coverage path planning is to cover target area as quickly and completely as possible.

To accomplish some probable level of guaranteed coverage, most of coverage path planners use cell decomposition method for separation of given space. The main idea of cell decomposition is to decompose a given bound space into a set of non-overlapping regions where each region is termed cell. Cell decomposition is generally classified into three classes [1], exact cell decomposition [2], approximate cell decomposition [3] and semi-approximate cell decomposition [4] according to separation rule. The exact cell decomposition method decomposes the configuration space into convex polygons of various shapes and sizes [5]. Boustrophedon and Morse decomposition belong to this category, which are introduced by Choset [2] and Acar [6]. Approximate cellular decomposition utilizes a fine grid to represent the free space. Here, the cells are all of the same size and shape, thus their union only approximates the space. The spanning tree covering (STC) approach [7] and backtracking spiral algorithm (BSA) [8] achieve online coverage based on this decomposition. Finally, semi-approximate cellular decomposition uses a partial discretization of the space, in which the cells are fixed in width but can have any shape at the top or bottom. To cover a space, the robot traverses along a series of parallel straight lines that divide the space. Each region is then covered using back-and-forth motion [4, 9].

To achieve the cell decomposition in real time process, problem is going to be computationally large and retains more information of the map that is more accurate. One of methods for localization and mapping is using laser image matching which is to determine N dimensional rigid transformation for given two sets of N dimensional data (i.e. a reference data set and a current data set). In fact, algorithms based on iterative closest points (ICP) [10, 11], polar scan matching [12], Hough scan matching [13], histogram based methods [14, 15] and other effectiveness algorithms have been used. One of popular approaches to solve the problem is the ICP technique introduced by Li [10] and Lu [11] that breaks down the registration of arbitrary geometric features into aligning the points defining these instances and formulates an alignment error in terms of a point to point metric.

Additional extensions to the ICP algorithm address to improve performance and robustness of the algorithm [13, 16, 17] exploited properties of Hough transform to determine linear transformation between consecutive scans. It does not consider geometric primitives from scanned data therefore it is robust to sensor noise. Attribute of the Hough scan matching

from others is it able to get several estimates of the rotation by comparing the spectra which defined from Hough transform of both scans. Most easy way to performing that scan data registering is histogram based method [14, 15]. The basic idea of the histogram matching approach is to find characteristics that remain unchanged over several scans that were taken in same environment but from different position and from different angles. Over all above methods have been capable to recovering robot motion and build its surrounding map with their different effectiveness and performance. This key point of the scan matching methods allow to us to achieve online cell decomposition and coverage path planning.

Recently, there are number of online cell decomposition approaches have been developed [18-21]. Similar to the cell decomposition, sector-based online coverage algorithm is proposed [18]. In this method, a target workspace is decomposed by sectors those are flexible regions. Sectors are created incrementally as the robot systematically explores the unknown workspace. Then the algorithm utilizes approximate cell decomposition method to plan a path. The virtual door based algorithm is introduced to achieve cell decomposition [19] where, the virtual doors are extracted by combining a generalized Voronoi diagram (GVD) and a configuration space eroded by the half of the door size, and the region to region cleaning algorithm is also proposed based on the closing and opening operations of virtual doors. To guarantee coverage in grid map representation, approximate cellular decomposition methods, including spiral-STC [7], backtracking spiral algorithm [8] and linked spiral path [20] are all based on low-resolution grid map representation, where the cell size is set to the size of the sweeping tool. Also, high-resolution grid map representation based approach is presented [21], where the cell size is smaller than the tool size.

In this paper, an adaptive cell decomposition algorithm for online coverage path planning is to be developed. In order to reduce computational load, it is needed to simplify strategies for path planning, map building and position correction under the assumption that the environment is rectilinear and closed. Position estimation of the robot is predicted by intensity-ICP algorithm and furthermore a map is built by online, because intensity-ICP algorithm has advantage to searching correspondence points. Main idea of the adaptive cell decomposition method is based on boustrophedon cell decomposition, which is implemented in [23]. To get reasonable map information that can be directly used for cell decomposition, line features and virtual lines are obtained from the collected map information. These are utilized to compose boundaries of cells. Capability of composing cell is depending on detection range of the laser scanner, therefore efficiency of the algorithm also is relates to the detection range. The robot simultaneously explores and covers the target space by adaptive cell decomposition method. The coverage path inside a cell is made of simple back and forth motions those were introduced as template based paths [22].

II. LASER IMAGE REGISTRATION USING THE INTENSITY-ICP

As an extension of the ICP-algorithm, intensity-ICP algorithm is proposed in this paper. It uses reflection intensity information of a laser scanned image, compared to most of scan matching algorithm just based on range image that recorded by laser scanner. For given two data sets those are the reference data set S_r and the current data set S_c, conventional ICP algorithm iteratively minimizes an alignment error E given (1) by conducting the following steps:

$$E_k = \sum_{i=1}^{N} \{(x_p(k) - x_q(k))^2 + (y_p(k) - y_q(k))^2\}, \qquad (1)$$

where N is the number of corresponding points between the reference data set S_r and the current data set S_c, k is the number of iteration, and $(x_p; y_p)$, $(x_q; y_q)$ are coordinates of the corresponding points in the reference data set S_r and the current data set S_c, respectively.

In the first step, the coordinates of the current data set are transformed by using homogeneous coordinate transformation matrix H. The matrix is initially calculated with the relative position information between the current data set and the reference data set which is supplied by an odometer. In the second step, the algorithm searches corresponding point pairs between the reference data set and the current data set.

The corresponding point of the reference data set to a point of the current data set is one which has the shortest geometric distance between them. It is determined by a nearest neighbor search.

That is, for each point of the data set S_c that is to be registered, the closest point in the data set S_r based on the point-to-point metric information is the corresponding point. In the third step, it calculates homogeneous coordinate transformation matrix H which minimizes error function (1).

After the third step, it returns to the first step, and transforms the coordinate of the current data set S_c using the homogeneous coordinate transformation matrix H which was obtained at the third step. The

algorithm repeats these steps until the termination condition is satisfied. In these steps, calculation of the homogeneous coordinate transformation matrix H converges.

The homogeneous coordinate transformation matrix H means re-localizing the position of the current data set was recorded.

The conventional ICP scan matching algorithm does not consider laser reflection intensity, so it cannot find correct corresponding point pairs between the reference and the current data set. But, because the intensity-ICP counts on the laser reflection intensity, it can correctly find correspondence point pairs.

Fig. 1 shows the difference of the conventional ICP and the intensity-ICP, where points denoted by red color are the reference data set and points denoted by black one are the current data set. In the figure, value of laser reflection intensity is denoted with the different shape of the data point.

Therefore, this method correctly searches corresponding point pairs where each of pair has the shortest geometric distance and the smallest difference of laser reflection intensity between both data sets.

This is the key point of the intensity-ICP algorithm. The error function (1) is modified by (2) in the intensity-ICP algorithm.

$$E_k = \sum_{i=1}^{N} \{(x_p(k)-x_q(k))^2 + (y_p(k)-y_q(k))^2 + w\times(I_p(k)-I_q(k))^2\} \quad , \quad (2)$$

where w is the weighting factor of the laser reflection intensity, l_p and l_q are laser reflection intensity of the each point in both correspondence sets. The implementation result of the intensity – ICP is shown in the Fig. 2.

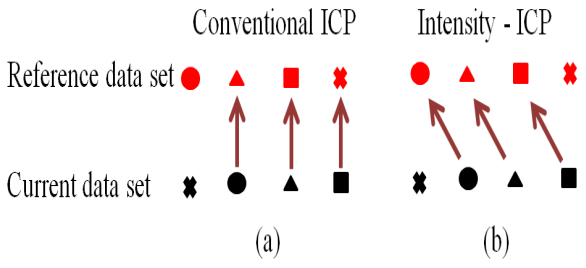


Fig. 1 Intensity – ICP algorithm. (a) The corresponding points are determined incorrect. (b) The corresponding points are determined correctly.

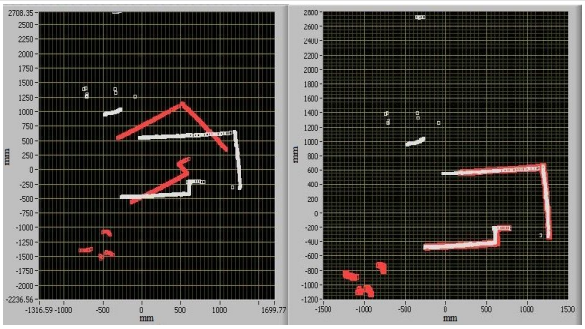


Fig. 2 The range image matching result using intensity – ICP algorithm.

A. Mapping and self-localization based on intensity - ICP

At the beginning of mapping and localization, the current position is usually initialized with (X, Y, □)=(0, 0, 0), and a range scan is taken and set as a reference map.

At the next scan after the robot is moving, a homogeneous coordinate transformation matrix H is obtained by executing intensity-ICP algorithm.
Then localization of the robot is updated and the environment map is incrementally built by (3) and (4), respectively.

$$\begin{bmatrix} X_{k+1} \\ Y_{k+1} \\ \theta_{k+1} \end{bmatrix} = \begin{bmatrix} X_k \\ Y_k \\ \theta_k \end{bmatrix} + \begin{bmatrix} \cos(\theta+\Delta\theta) & -\sin(\theta+\Delta\theta) & 0 \\ \sin(\theta+\Delta\theta) & \cos(\theta+\Delta\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} \Delta X \\ \Delta Y \\ \Delta\theta \end{bmatrix}, \quad (3)$$

where $\Delta X, \Delta Y$ and $\Delta\theta$ are the estimated pose change of the robot from the homogeneous coordinate transformation matrix.

$$S_r(i) = S_r(i-1) \cup \{(x_q, y_q) \mid \nexists (x_p, y_p) \in S_r(i-1) : \square(x_q, y_q) - (x_p, y_p) \square < d_{th}\} \quad , \quad (4)$$

where d_{th} is the threshold value for map merging.

The accuracy of the mapping depends on the estimated pose change and map merging process. The map merging is combining process of the reference data set S_r(i-1) and the current data set S_c(i) to get the reference data set S_r(i) of the next time step. Efficient decision is needed to figure out from the current scan which points are outlier points and which ones belong to new information of the environment those can be integrated with the reference scan for the map merging process.

A sparse point map is used to avoid duplicate storage of points by conducting additional correspondence search and counting out overlapped points those are the same points already stored in the map. A problem of the sparse point map procedure is its scalability with respect to the size of the environment and the number of scanned points.

By setting proper value of d_{th} according to the accuracy of the range sensor, overlapped points can be exactly determined and duplicate storage of one and the same point assuming correct alignment of range scans. Choosing, however, a larger value allows reducing the number of points stored in the map (Fig. 3(a)). At this point, we use simple rule, where to find duplicated points qi in the current data set, current center point pi and both sides points p_{i-1} and p_{i+1} are used to check them as displayed in Fig. 3(b). If the Euclidian distances between center point pi and p_{i-1} and p_{i+1} are less than threshold value d_{th}, points in the current data set which are inside of the circle are deleted. In this case, those points are assumed as duplicated point in the reference data set (Fig. 3(b): 1, 4). Otherwise, points are assumed as new information because those are not duplicated to the points in the reference data set (Fig. 3(b): 2, 3). This way duplicated points and new data points are efficiently found and the reference data set and new data are merged correctly (Fig. 3(b): 5).

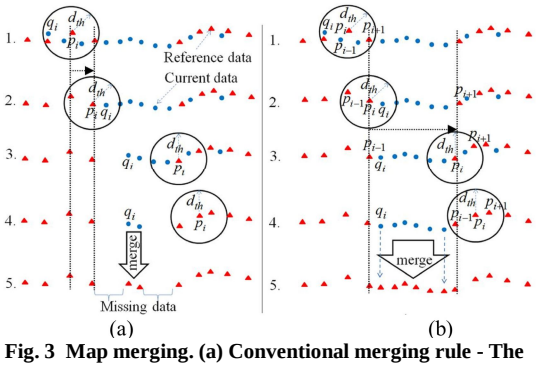


Fig. 3 Map merging. (a) Conventional merging rule - The red is the reference data set, the blue is the current data set. 1) ~ 4) Points in the current data set, which are placed inside of the circle with pi center point and dth radius, are deleted. These are assumed as duplicate points. 5) The reference data set and current data set are merged but some points in the current data set are missed. (b) Modified map merging rule - 1) and 4) Points in the current data set which are located inside of the circle, are deleted because elimination condition is met. 2) and 3) Points in the current data set which are located inside of the circle are not deleted. These are new information of the workspace because elimination rule is not met. 5) Both data sets are merged efficiently

III. ADAPTIVE EXACT CELL DECOMPOSITION

The basic idea of the conventional adaptive cell decomposition approach is to reduce the number of cells used in free space in order to waste less memory storage space, computation time and to remove the digitization bias of the regular cell decomposition. The most common type of adaptive decomposition is a quad-tree decomposition, it is similar to the approximate cell decomposition. The adaptive cell decomposition imposes problems for dynamic environments where the robot is acquiring new data and updating its map based on unexplored space. When this happens, it is necessary for the entire data structure of the map to be revamped.

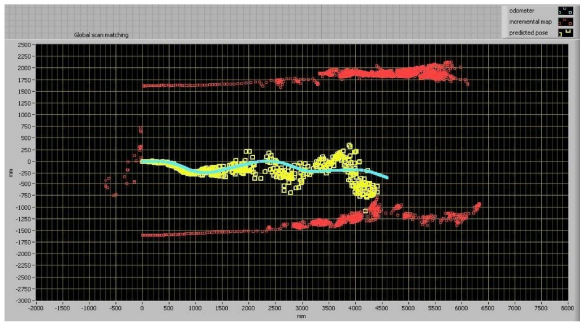


Fig. 4 Mapping and localization result

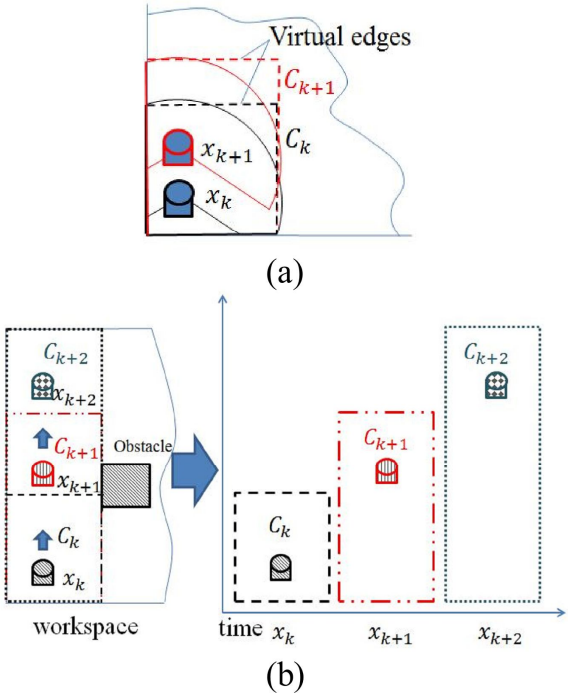


Fig. 5 Adaptive cell decomposition. (a) concept of virtual edge. (b) Inheritance of the cells.

Our problem statement in this paper comes from above assumption. Therefore, we aim to develop adaptive cell decomposition algorithm for online coverage path planning. But we term other definition for the adaptive cell decomposition, where cell is composed during the robot's motion. On the other hand cells are composed from revamped map.

The definition of the proposed algorithm is shown in the Fig. 5(a) where the robot's current position is x_k and future position is denoted by x_{k+1}. Assume that robot acquires data of the workspace and composes cell C_k at position x_k. But when the robot is moved to the position x_{k+1}, it can have more data to be gathered from the unexplored contours of the workspace. At this time, cell C_k is updated by new cell C_{k+1}, it to be bigger than previous cell C_k. Because the robot have updated or revamped map data of the workspace, then

cell decomposition is performed to get cell C_{k+1}. In order to employ idea of adaptive cell decomposition, we define some assumptions. First workspace of the robot is rectilinear and enclosed to reduce computational load of the real-time process. Second, cells are composed adaptable for explored map, which means cell is composed and is updated until it is unchanged.

This assumption is introduced by Fig. 5(b). For instance; the robot's position is given by x_k, x_{k+1} and x_{k+2}, in several times. For each position, robot takes measurement and composes cell such as C_k, C_{k+1} and C_{k+2} in the Fig. 5(b). The cell C_{k+2} is an inheritance cell of the cells C_k, and C_{k+1}. If there is a no changing in the cell boundaries, then the inheritance of that cell is finished. That meaning is that cell is composed successfully because no changes in its boundaries. This assumption is shown in the Fig. 6 where the last inheritance of the cell C_k is C_{k+2}. The termination condition of the inheritance is determined to compare width w_k and length l_k of the cells. Even though, there are still existing errors in real, therefore we use some error interval for the comparing the cell parameters regarding the sensor error. Third, virtual edges and line features used to compose cells. To get these, line features and virtual lines are obtained from collected map information.

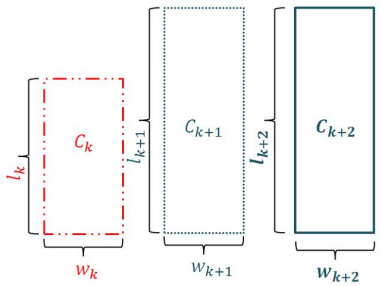


Fig. 6 Termination condition of the inheritance. If the length and width are unchanged or small changed, the inheritance is finished.

The line features are obtained by using line fitting. To obtain the virtual line, we first explain the basis of the proposed method. It comes from boustrophedon cell decomposition, which is implemented in [23]. The boustrophedon cell decomposition is based on sweep line which sweeps through a bounded workspace populated with polygonal obstacles. When the sweeping line encounters the edge of the obstacle, new boundary of the cell is determined. Furthermore boustrophedon approach related to the events to compose cells, these are explained more detailed in [2]. Similarly, cell boundaries are determined by extending critical edges which called virtual edge. The concept of the critical edge is defined in [24] where the robot senses contours of wall and/or objects in the workspace which are termed critical edges.

We explained the map merging process in section II, but before apply it, we need to align the new data segment to its corresponding segment in the map in order to reduce accumulating error for the map (Fig. 7). Because we need to reasonable map information that can be directly used for cell decomposition. After segment correction, then the map merging is done and robot decomposes the given map into cells by boustrophedon cell decomposition.

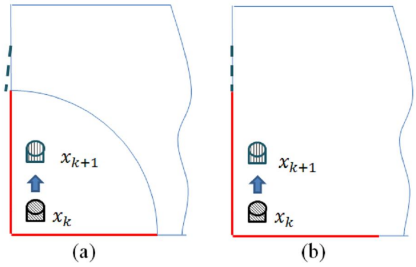


Fig. 7 Map updating process. New acquired data segment is aligned to the corresponding line segment. (a) before correction. (b) after correction.

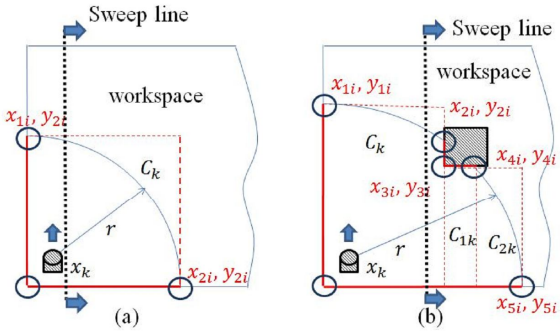


Fig. 8 Cell composing process. (a) Obstacle is not detected. (b) Obstacle is detected

Fig. 8 depicts cell composing process. With the sweeping line, position of the virtual edge is found but to determine this, starting and ending points of the segments are needed to be obtained from the map. The starting and ending points are marked as circles in the Fig. 8. Capability of the composing cell is depending on detection range of the laser scanner, therefore efficiency of the algorithm also relates to the detection range. The coverage path inside of the cell is based on simple back and forth motion as same as template based path planning that introduced in [23].

IV. EXPERIMENT

The proposed adaptive cell decomposition algorithm is tested through a mobile robot equipped with a 2D laser scanner URG-LX04, which moves across an experimental workspace with size 6.5 m × 4.1 m. While the robot is moving, the laser range sensor provides a bearing-plus-range measurement at a 10 Hz sampling frequency with a 180° field of view. The initial displacement of the robot is obtained by the

odometer. The maximum linear and angular speeds of the robot are 0.226 m/sec and 0.78 rad/sec, respectively. The algorithm runs in real time, and no more than 50% of CPU computation is used for the entire mapping and the adaptive cell decomposition algorithm.

As explained in Section II, the incremental map is built on the basis of the scanned data points. The initial incremental map is a point map as shown in Fig. 9(a). Figs. 9(a, c, e) show each step of the robot's movement through the workspace, and Figs. 9(b, d, f) denote the corresponding results of the proposed algorithm at each step. Each part of Figs. 9(b, d, f) indicates how the robot reacts as the measured workspace changes with the proposed approach. The proposed approach allows the composition of cells of any shape, such as a triangle, rectangle, and polygon, as shown in Figs. 9(b, d, f). Also some cells are composed with part of the curve as shown in "Cell6 and Cell7" in Fig. 9(d & f). A comparison of Fig. 9(b) with Fig. 9(d) shows that the cell update is working, and the adaptive cell decomposition is executed well with the shape change of the decomposed cell.

When the task of coverage path planning is given to a robot, it should perform map building first before executing localization and planning its coverage path within the explored area. Thus, time performance is another issue because the robot executes these tasks successively. However, the proposed algorithm can reduce and save the task time within an unknown workspace because the robot can react to every change of the environment of the workspace using the proposed algorithm. The time consumption of this approach is low because the methodology of the proposed algorithm is simple. The proposed algorithm permits the robot to perform the three missions of localization, mapping, and planning at the same time. Thus, the adaptive cell decomposition has advantages in relation to time and energy efficiency during the whole process.

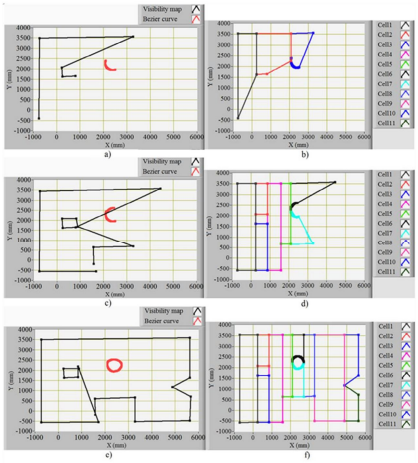


Fig. 9 Experimental result of the proposed approach.

The main characteristics of the conventional exact cell decomposition are usually defined using small features, such as vertices in trapezoidal decomposition (Choset 2000) and critical points in Morse decomposition (Acar et al. 2002). By contrast, the main characteristics of the adaptive cell decomposition are defined using large features and segments. For example, obstacle segments are detected in terms of their proximity to obstacles along the sweep line (Wong et al. 2003). These large features have physical attributes that are detectable over time. The boustrophedon decomposition can handle only polygonal obstacles. The Morse decomposition is more general than the boustrophedon decomposition and can handle obstacles with curved contours. However, it is effective only for non-rectilinear environments because boundaries parallel to the sweep line are considered degenerate cases for Morse functions. The adaptive cell decomposition can handle any environment with objects that have polygonal, curved, or rectilinear contours.

CONCLUSION

Cell decomposition is a well-known method that provides an effective path planning for an area covered by a mobile robot. The final goal of this research is to develop a simple and robust method for the performance of OPP for an unknown workspace assigned to a mobile robot.

The contribution of this paper is the development of an online adaptive cell decomposition method for a mobile robot working in an unknown workspace, where the robot is placed at an unknown initial pose. The ICP registration method, combined with the nearest neighbor search, is responsible for the mapping and localization of the robot. The visibility map for path planning is constructed based on the concept of feature extraction and the characteristics of the corresponding pair of features. The scanned data points inherently contain a considerable amount of noise.

The sensor noise is also filtered for feature extraction with the least amount of computation. Keeping the features in the memory and searching for the corresponding feature pairs can be achieved easily because comparatively, only a slight amount of memory is needed to keep the four values for line feature and 100 values for curve feature required.
The adaptive cell decomposition approach is applied to discretize the visibility map into non-overlapped cells. The experiment result shows that the adaptive cell decomposition works effectively and the coverage path planning can be integrated with the proposed method.

The proposed algorithm also permits the robot to perform the localization, mapping, and planning tasks at the same time. The main advantage of the adaptive cell decomposition method is time efficiency, which results in efficient energy consumption during the entire process.

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