Path and Observation Planning of Vision-based Mobile Robots with Multiple Sensing Strategies[1]

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Abstract. In this paper, we propose a new path and viewpoint planning method for a mobile robot with multiple observation strategies. When a mobile robot works in the constructed environments such as indoor, it is very effective and reasonable to attach landmarks on the environment for the vision-based navigation. In that case, it is important for the robot to decide its motion automatically. Therefore, we propose a motion planning method that optimizes the efficiency of the task, the danger of colliding with obstacles, and the accuracy and the ease of the observation according to the situation and the performance of the robots.

Keywords. Path planning, Viewpoint planning, Mobile robot, Landmark

1. Introduction

In this paper, we propose a new path and viewpoint planning method for a mobile robot that has two active cameras according to the performance of the robot.

The robot navigation is a very important technology to execute various tasks. The navigation is usually executed while the robots move and estimate their positions and orientations by using the information from several sensors.

A dead-reckoning is a method that can estimate the robot position and orientation with internal sensor. However the error of it is accumulated in proportion to the traveling distance and the recovery of the error is impossible only with internal sensors.

Therefore, external sensors are always utilized for the robot navigation. The robot can observe landmarks in the environment and measure the relationship between these points and the robot itself in the image-based navigation. When the robots observe them, the problems are how to measure the accurate position and orientation of landmarks, and where and which landmarks the robots should observe while there are multiple landmarks.

As to the former problem, there are a lot of studies that improve the accuracy of 3-D measurement, *i.e.*, [1]. However, there is a limit in accuracy when the robot always observes the same landmark regardless of the distance between the robot and the landmark.

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Therefore, the latter problem is very important for the robot navigation. This means that the robot must decide the path and choose the observing landmarks according to its position while it moves[2]. Navigation planning methods under the uncertainty are also proposed[3]-[6].

On the other hand, the design of the optimal arrangement of artificial landmark is very important in the indoor environment[7]. Takeuchi *et al.* proposed a method to dispose artificial landmarks in the environment, and to navigate a mobile robot there[8]. The landmarks are disposed so that the robot can observe at least one landmark at any positions, and the robot plans the observation so that they can observe landmarks.

2. Purpose

We have already proposed the landmark observation method with multiple strategies[9]. In [9], the robot used the C-obstacle (configuration obstacle) to escape the danger of the collision with the obstacle, and the only width of the expansion of C-obstacle was decided. However, when the given environment is complex, deciding the expanding width becomes difficult. If the expanding width of C-obstacle was unsuitable, the robot was not able to reach the destination, or it had to travel unnecessary long moving distance. Therefore, the robot had to look for appropriate expanding width of C-obstacle. Then, the robot in this work searches for the path of the expanding width of two or more C-obstacles, and discovers the path in appropriate width among that. In this method, a primary value of the expanding width of C-obstacle is given to the robot, and the robot continue to increase constant width about the expanding width of C-obstacle. The robot searches for the path in the expanding width of each C-obstacle. When the path that can be connected with the destination is not found, the robot ends the search for the path.

Using observation technique of [9], we propose the improvement technique for path planning. We make the shape of C-obstacle better. In [9], the vicinity of the vertex of C-obstacle has been expanded more widely than original expanding width. Therefore, there was a problem to which it was not able to pass in the path that should be able to pass. In this work, the corner of C-obstacle is expressed by the polygon. The expanding width in the vicinity of the vertex approximates to original expanding width by this method, and solves problem of [9]. In [9], the n-th shortest paths were searched in each visibility graph by a simple brute force method. In our path planning, the path is planned by Dijkstra algorithm. Even if the combination of all the vertices is not confirmed, this technique can discover the shortest path. As the result, the amount of the path searching is decreased.

Optimal path and viewpoint planning is necessary for the robot to execute works efficiently. At the same time, “optimal” path and viewpoints change according to the performance of the robot. Some previous works can plan the optimal paths and viewpoints of the robot [10]. However, they don’t consider the relationship between optimal planning results and the performance of the robot explicitly. For the robot with good performance, path can be planned by giving priority to moved distance more than safety. On the other hand, the robot with bad performance will be able surely to reach the goal the plan of path to which it gives priority to safety. Therefore, “optimal” path and viewpoints depend on the performance of the robot. There are multiple evaluation methods such as high accuracy, path length, and safety. Evaluation methods also change when the performance changes. Therefore, we propose a new path and viewpoint planning method for a mobile

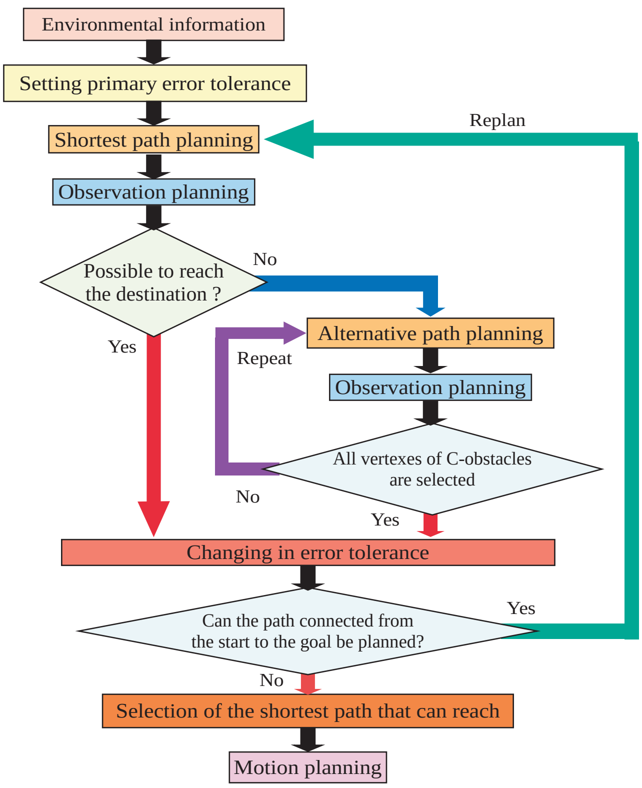


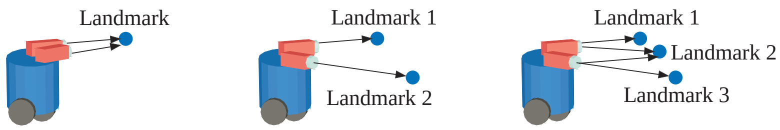
Figure 1. Path and observation planning.

robot with multiple observation strategies according to the performance of the robot. We verify the effectiveness of this method through simulations.

The accuracy of multiple observation strategies depends on the positions of landmarks that can be observed. Therefore, the robot must choose the optimal landmark-observation strategy to consider the number and the configuration of visible landmarks in each place. The path and viewpoints are planned by considering not only the accuracy of the optimal observation strategy but also the dead-reckoning error of the robot also plans the path and viewpoints.

Our motion planning method is designed to guarantee that the robot never collides with obstacle. The robot selects the shortest path from the safe paths. After deciding the shortest path, the number of viewpoints is minimized. This is because it is desirable that the cameras equipped with the robot are utilized for the other uses of the landmark-observation.

The motion planning begins from the input of environmental information including the landmark position, the start position, the goal position, and the extra information to the robot (Figure 1). The shortest path and the viewpoint are planned from input environmental information. As for shortest path, it is distinguished whether to reach the goal without colliding with the obstacle by the observation plan. When it is possible to reach goal position, error tolerance is changed and it plans from the shortest path plan again. When it is not possible to reach the goal, paths other than shortest path are planned and



(a) Stereo observation. (b) Two-landmark observation. (c) Three-landmark observation.

Figure 2. Three observation strategies.

the viewpoint of those is planned. Shortest path that can reach the goal in searched path is assumed to be optimal path.

3. Three Observation Strategies

3.1. Problem Statement

We make the assumptions for the planning of the robot navigation. The robot can move in all direction at any time and uses the information from two active cameras that can change their directions independently. The shape of the robot is expressed as the circle whose radius is R. The environment map that indicates the positions of walls, obstacles, and landmarks is also previously provided to the robot. Therefore the map is available in the robot. All landmarks whose heights are same with those of robot's cameras are attached to the environment. The shape of the landmark is a circle and the radius of each landmark is constant. Each landmark can be distinguished with each other. The detail of each error of the observation is explained in [9].

We develop three observation strategies: (a) stereo observation, (b) two-landmark observation, and (c) three-landmark observation (Figure 2).

3.2. Stereo Observation

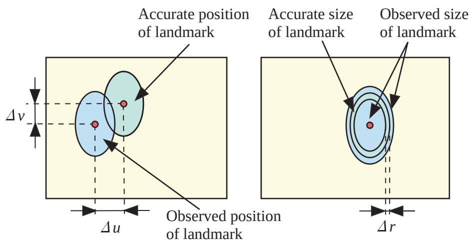
The stereo observation can be executed when one or more landmarks are inside the robot's field of view. The robot estimates its position and orientation with the triangulation. In this strategy, the 3-D positions of left and right ends of the observed landmark are measured with the information of disparities. The position and orientation of the robot in the world coordinate can be calculated from the coordinate value of two points.

3.3. Two-Landmark Observation

The two-landmark observation can be executed when two or more landmarks are inside the robot's field of view. Left and right ends of the nearer landmark and a center point of the distant landmark are extracted from two acquired images. This observation calculates only angle information from that image. The position and the orientation of the robot in the world coordinate can be decided as a result.

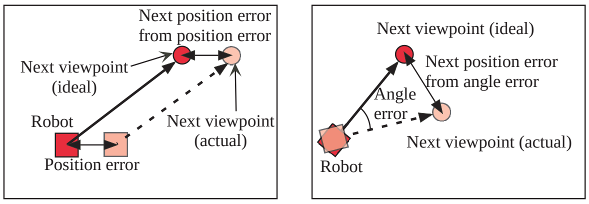
3.4. Three-Landmark Observation

The three-landmark observation can be executed when three or more landmarks are inside the robot's field of view. The relationship between three landmarks and the robot is estimated from the coordinate value of the center of three landmarks in images.



(a) Position error. (b) Size error.

Figure 3. Image error.



(a) Position error. (b) Orientation error.

Figure 4. Position and orientation error of robot.

The accuracy of the estimated position and orientation become higher as compared with two-landmark observation method. This is because the distance between the extracted points in images is larger in three-landmark observation than in two-landmark observation. In addition, the image noise at the edge of the landmark is generally larger than that at the center, because the coordinate value of the center position in the image coordinate can be obtained accurately by calculating the center of gravity of the pixels that belong to the landmark.

3.5. Optimal Observation Strategy

The robot chooses the optimal landmark-observation strategy that can estimate its position and orientation precisely. The optimal strategy can be decided when the path and the position of the viewpoint is planned.

At first, the visible landmarks in each place are selected to consider the robot's field of view. The robot cannot observe landmarks when obstacles are between the robot and landmarks and cannot observe them from the back side.

Incidentally, the error of image such as quantization error always occurs. Then, the theoretical estimation errors of robot's position and orientation are calculated by considering the situation that the errors of landmark's position and size (shape) in images occur (Figure 3).

We assumed that the position error of the landmark's center point in the image is $(\Delta u, \Delta v)$. The size error of the landmark in the image Δr is also considered. It means that the observed landmark's position in the image may shift $(\pm\Delta u, \pm\Delta v)$ from the true position at the maximum. The observed radius may also shift $\pm\Delta r$ from the true size.

The robot estimates how the position and orientation errors occur in the world coordinate about all combination of visible landmarks when the errors occur in the images (image coordinates) of two cameras.

However, the position error and the orientation error are not compared directly because the dimensions of them are different from each other. The position error is expressed as the dimension of length, *i.e.*, [mm], and the orientation error is expressed as the dimension of angle, *i.e.*, [deg].

Therefore, we transform the orientation error (the dimension of angle) into the position error (the dimension of length). The total sum of the error when the robot moves at a certain distance while the position and orientation error occur is calculated (Figure 4). This means that the total error at the next time's position of the robot when it moves is the sum of the position error ($E_{pos,\max}$, Figure 4(a)) and the incorrect moving distance under the influence of the orientation error ($E_{ang,\max}$, Figure 4(b)). $E_{pos,\max}$ is the distance between the ideal robot position without error and the real position with error derived from position error. $E_{ang,\max}$ is the distance between the ideal robot position without error and the real position with error derived from orientation error. Therefore, $E_{pos,\max}$ and $E_{ang,\max}$ have the same dimension of length.

In this way, the estimated error of the robot position in the world coordinate that is caused by the image error is calculated. The optimal observation strategy is equal to the observation method that has minimum position estimation error.

The optimal observation strategy is decided as follows:

$$\begin{aligned} E_{\max}(p,m) &= E_{pos,\max}(p,m) + E_{ang,\max}(p,m) \\ &\rightarrow \min, \end{aligned} \tag{1}$$

where p is the present position, m is the moving distance, and $E_{\max}(p,m)$ is the total error when the robot move distance m from p.

The direction of two cameras is decided by selecting the optimal observation strategy in each place. Therefore, the navigation planning of the mobile robot can be executed.

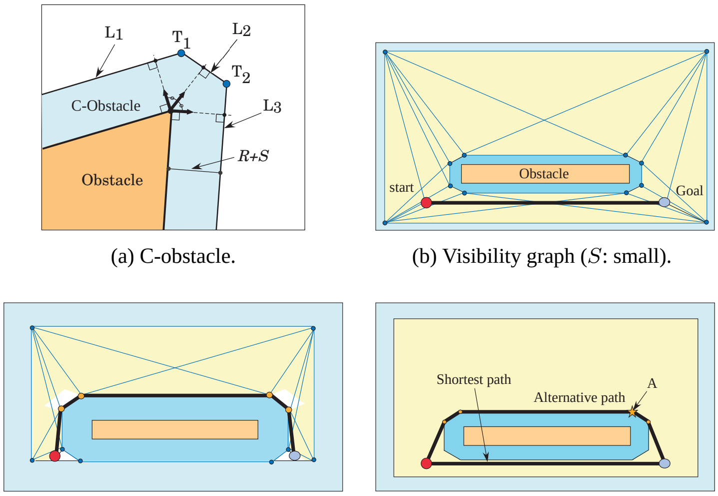
4. Path and viewpoint Planning

4.1. Path Planning

The path of the robot is planned based on the visibility graph.In our motion planning method, original obstacles are expanded $R + S$ where S is the margin for safety (Figure 5(a)). In this paper, we call S the error tolerance. When generating C-obstacles, shapes of their vertices are approximated with the polygons because of simplicity of computations. Therefore, their vertices were approximated to intersection T_1, T_2 of $L_i (i = 1, 2, 3)$.

The vertices of C-obstacles are connected with each other and a visibility graph is constructed (Figure 5(b)). In this step, multiple visibility graphs are generated by changing S for optimal planning. This is because it is difficult to find the best S in complex environment beforehand. The robot of bad performance can plan path that safely reaches the goal by changing S(Figure 5(c)).

In each visibility graph, the shortest path from a start position to a goal one is searched by Dijkstra algorithm (Figure 5(d)). However, the robot cannot necessarily



(a) C-obstacle.

(b) Visibility graph (S: small).

(c) Visibility graph (S: large).

(d) Shortest path and alternative path.

Figure 5. Expanded C-obstacle and path planning.

move along the shortest path due to its performance and the configuration of obstacles and landmarks, and several candidates of path must be prepared. Therefore, to search for paths other than shortest path by Dijkstra algorithm, the vertex of C-obstacle is chosen at random as a relay point($= A$) of the start position and the goal one. About the relay point, path from start position to A and path from A to goal position are searched by Dijkstra algorithm. The paths are composed by the connection of them. In this paper we call them alternative paths. Path for which it searched by choosing the relay point at random and quite different path can be planned.

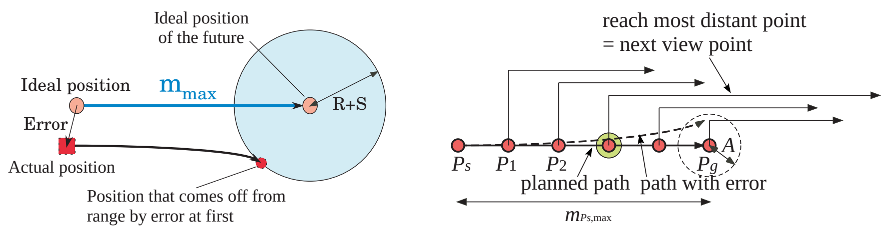
4.2. Viewpoint Planning

Viewpoint is planned about each path that is planned in the previous step. Viewpoint planning for arriving at the goal position safely is executed by considering the observation error of landmarks and dead-reckoning error.

The robot estimates its position and orientation by dead-reckoning while moving after observing landmark(s). If it moves long distance after estimating its position with landmark(s), the error of estimated position and orientation is accumulated in proportion to the traveling distance. Therefore, the robot must estimate its position with landmark(s) frequently before position error is accumulated.

Here, it is assumed that the robot observes landmark(s) where the distance between the present position p_s and the start position is m_s along the planned path. Let $D_{\max}(p_s, m)$ be the estimated maximum dead-reckoning error when the robot move distance m from p_s, $E_{\max}(p_s, m)$ be the estimated maximum error from the observation (1), and S (error tolerance) means the maximum error of the robot position for not colliding with obstacles. The maximum distance m_{max} that the robot can move without observing landmarks is expressed as follows (Figure 6(a)):

$$D_{\max}(p_s, m_{max}) + E_{\max}(p_s, m_{max}) \leq R + S. \qquad (2)$$



(a) Distance that can be moved without observation.

(b) Selection of view points.

Figure 6. Observation planning

Here, let p_g be the position whose distance from the start is $m_s + m_{p_s,\max}$. The path from p_s to p_g is divided into $n + 1$ position, and we define m_i as the distance between the each divided position p_i and the start position of the path ($p_0 = p_s$, $p_n = p_g$).

When the next viewpoint from p_s is p_i, the next viewpoint from p_i must satisfy the following equation when the total number of observation becomes small (Figure 6(b)).

$$m_i + m_{p_i,\max} \rightarrow \max\,. \tag{3}$$

The robot selects the optimal landmark-observation strategy that satisfies (3). Therefore, the viewpoints can be decided one by one in the following way.

1. $m_{p_s,\max}$ and p_g that satisfy (2) are calculated when the robot observes landmarks at p_s.
2. The path from p_s to p_g is divided into $n + 1$ position p_i.
3. p_i that satisfies (3) is calculated, and p_i is regarded as the next viewpoint.
4. If $m_i + m_{p_i,\max}$ is smaller than the distance between the start position and the goal position of planned path, p_s is replaced with p_i and go to step 1). If it is large, the viewpoint planning finishes.

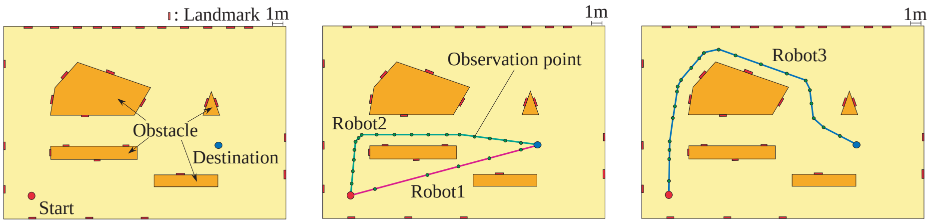
The optimal viewpoints, the optimal observation strategies in each viewpoint, the optimal observed landmark(s) and the direction of the cameras in each viewpoint could be planned in the above procedure.

5. Results of Motion Planning

In this section, the effectiveness of the motion planning by the difference of the performance of the robot is verified. In this paper, robot performance means dead-reckoning error and image error. The dead-reckoning error shows at the rate how much error occurs about moving distance. The image error shows the position's error of the landmark and the size error of the landmark. Figure 7(a) shows environment. The primary value of the

Table 1. Robot performance.

Name	Dead-reckoning error	Image error
Robot1	$\pm$10 %	$\pm$1 Pixel
Robot2	$\pm$40 %	$\pm$1 Pixel
Robot3	$\pm$40 %	$\pm$5 Pixel



(a) Environment. (b) Robot1 and Robot2 path. (c) Robot3 path.

Figure 7. Simulation results.

Table 2. Comparison of path.

Name	Error torelance (cm)	Distance (cm)	The total number of observation
Robot1	60	2359	6
Robot2	120	3246	19
Robot3	150	5140	31

expanding width of C-obstacle is decided to S=0cm, and the increasing constant width is decided to 30cm. We compare Robot1 whose dead-reckoning error and image error is small, Robot2 whose dead-reckoning error is large, and Robot3 whose dead-reckoning error and image error are large, for evaluating the relationship between the planning result of the path and the viewpoints and the performance of the robots (Table 1).

As the result of planning, Robot1 and Robot2 can reach the goal along the paths shown in Figure 7(b). In addition Robot3 can reach the goal along the path shown in Figure 7(c). The path of Robot1 is narrow and the landmark that can be observed is few. However, because the dead-reckoning performance of Robot1 is good, the path planned can be traced accurately. Moreover, because the observation accuracy is good, the error can be accurately corrected by a little observation frequency. On the other hand, because the dead-reckoning performance of Robot2 is worse than Robot1, it cannot trace accurately the planned path. Therefore, it cannot plan the path of Robot1. In addition, the path reaching the destination was not found at this error tolerance (=60cm). Then, error tolerance is changed, and Robot2 plans the path with wide width of the road though the distance of it is longer than the path of Robot1. Moreover, because the dead-reckoning performance of Robot2 is bad, it should correct frequently the dead-reckoning error by observing the landmark. As a result, the observation frequency of it is more than frequency of Robot1. The path of Robot3 is wide and landmarks that can be observed are many. Because the dead-reckoning performance and the observation accuracy of Robot3 are worst, it cannot be moved along the planned path. Therefore, it plans the path that safely reaches the destination though moving distance becomes long. In addition it is understood that Robot3 observed a lot of landmarks and moves along the route.

From these results, it is shown that the optimal path observation points, observation strategies can be planned according to the performance of the robot. In concrete terms, the robot with high performance (small dead-reckoning and image error) can select the short path from the start to the goal, although there are few landmarks and this is a dangerous path. Contrarily, the robot with low performance selects the safe path in which a lot of landmarks can be observed and the accuracy of positioning is high, although the distance between the start and the goal is long.

6. Conclusion

In this paper, we propose a new path and viewpoint planning method for autonomous mobile robots with multiple observation strategies. The robot estimates its position by observing landmarks attached on the environments with two active cameras. It chooses the optimal landmark-observation strategy depending on the number and the configuration of visible landmarks in each place. The optimal path, viewpoints, and observation strategies that minimize the estimation error of the robot position and the number of observation can be selected properly. The effectiveness of our method is shown through simulations.

As the future works, it should be better that models of sensor and motion error are based on probabilistic ones, such as Kalman filters, particle filters, SLAM.

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