Proceedings of the 8th Int. Conf. on Intelligent Autonomous Systems, pp. 873-880, Amsterdam, The Netherlands, March 2004.

Adaptive Robot Speed Control by Considering Map and Localization Uncertainty

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Abstract

This paper describes an adaptive robot speed control method for safe *and* efficient navigation in unknown environments. Speed control is important in the following two cases. (1) When a robot enters a narrow free space, it needs to control the speed to avoid any collision considering the motion uncertainty. (2) When a robot enters a region whose vacancy (i.e., being free) has not been decided yet, it needs to control the speed so that it can observe the region sufficiently to be confident with the vacancy of the region. This paper proposes a simple but effective strategy for speed control that the robot selects the *fastest safe speed*. To adopt this strategy, we define criteria for judging whether a speed is safe for the above two cases. The proposed method successfully made the robot move around in unknown static environments with adaptively controlling the speed.

1 Introduction

Mobile robot navigation in unknown environments has been one of the active research areas in robotics. Many previous works have been concerned with localizing a robot and/or generating a reliable map from uncertain data obtained by internal (e.g., odometry) and external (e.g., vision and sonar) sensors [3, 7, 16]. Their main focuses have been on developing methodologies for realizing accurate and reliable localization and/or map generation, given a sequence of sensor data and a set of sensor uncertainty models.

Sensor planning is also important in designing sensor-based robots operating under various uncertainties. In the mobile robot domain, some dealt with observation planning issues, especially planning methods for increasing the quality of maps (e.g., [1]) or for exploring unobserved spaces (e.g., [2]) or both (e.g., [4, 8]). The objectives of these planning methods are, however, mainly for obtaining more information. This paper, on the other hand, considers another aspect of planning, that is, a planning for increasing the efficiency of navigation.

Mobile robot navigation can roughly be divided into two levels: selecting a route and following the selected route. For the first level, there are some works on observation planning for realizing an efficient navigation. Several works have dealt with this route selection problem using a probabilistic model of sensor and motion uncertainties (e.g., [5, 10]).

For the second level (i.e., following a route), there are many works on visual feedback motion control (e.g., [12]); they are mainly concerned with development or application of control theories.

A certain level of accuracy in robot localization is indispensable for a safe navigation. Several works deal with landmark selection problems in which an appropriate set of landmarks is selected for minimizing the predicted localization uncertainty [13, 6]. If we consider

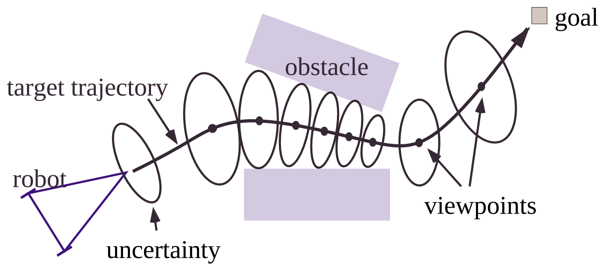


Fig. 1: An example od adaptive speed control. Viewpoint intervals are short in a narrow space.

the cost of sensing, however, observing uncertainty-minimizing landmarks may not be optimal in terms of the cost of reaching a destination; so it is necessary to consider what accuracy is needed in each situation.

A general goal of navigation methods is to realize a safe *and* efficient movement of a robot. *Safety* usually means that a robot does not collide with obstacles. On the other hand, *efficiency* here means that a robot can reach a destination in a small amount of time. These two requirements, safety and efficiency, are sometimes in a tradeoff relation. If a robot moves fast to increase efficiency, the number of observations usually decreases and uncertainties in state estimation such as a localization uncertainty thus increase; this most probably decreases safety. If a robot moves slowly to increase safety, efficiency will decrease.

To cope with this tradeoff, we proposed a strategy that a robot moves at the *fastest safe speed* [11]. That is, we first define a criterion for judging whether a speed is safe, and then select the fastest safe speed. Based on this simple but effective strategy, we can naturally realize an adaptive speed control as shown in Fig. 1; such a control is exactly the same as what we are doing in driving cars.

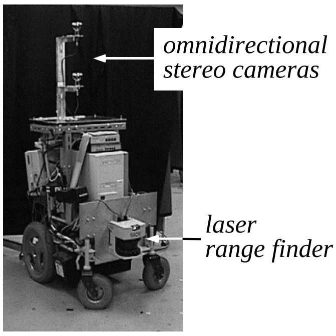
In [11], we developed a speed control method based on the distance to nearby obstacles in a *completely-known* environment. This paper extends the method to unknown environments. In such an environment, since a robot moves while incrementally generating a map, not only the distance to recognized obstacles but also that to *undecided regions*, which have not been sufficiently recognized as free, needs to be considered in robot speed control; it is not desirable for a robot to enter such an undecided region from the viewpoint of safety. An on-line path planning is also necessary in navigation in unknown environments.

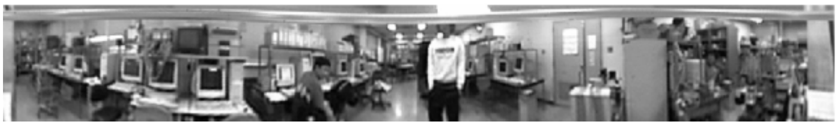
2 Map Generation by Integrating Omnidirectional Stereo and Laser Range Finder

This section briefly describes our map generation method using an omnidirectional stereo and a laser range finder. Please refer to [9] for the details. Our speed control method is designed by considering what result is obtained and how it is obtained by this map generation method.

Our stereo system uses a pair of vertically-aligned omnidirectional cameras (see Fig. 2). The system can generate a disparity image of 360x50 in size and 40 in disparity range in every about $0.1\,[s]$ (see Fig. 3). We also use a SICK laser range finder (LRF), which is set at the front of the robot so that it scans the horizontal plane at the height of $35\,[cm]$ from the floor (see Fig. 2). The resolution used is $1.0\,[deg]$ per point (i.e., 181 measurements for 180 degrees).

We keep a probabilistic occupancy map [3] for each sensor. Temporal integration of sensor data is carried out for each map separately using *forward sensor model*[14, 15]. We adopt the *independence assumption*; i.e., update the probability of a grid independently of other





(a) Panoramic image.

(b) Panoramic disparity image obtained from (a).

Fig. 2: Our mobile robot.

Fig. 3: Omnidirectional stereo generates a panoramic disparity image.

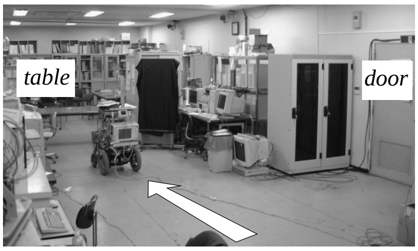


Fig. 4: An example scene.

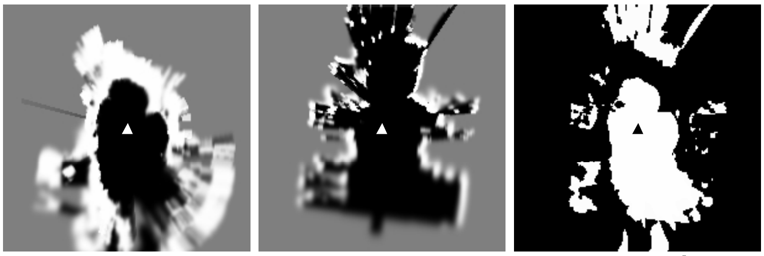


Fig. 5: Probabilistic maps and a free space map

grids. This assumption seems reasonable when a sensor has a fairly fine angular resolution.

The two probabilistic maps are integrated as follows. Since the two sensors may detect different objects or different parts of an object at a 2D position, a direct integration of probability values by the Bayes' rule is not appropriate [9]. We, therefore, first classify each grid of a map into four classes and then integrate the classification results into the free space map.

The classification is carried out in two steps. In the first step, we use two thresholds. If the occupancy probability of a grid is larger than the higher threshold (currently, 0.7), the grid is classified as *obstacle*; if the probability is less than the lower threshold (currently, 0.2), the grid is classified as *free space*; otherwise, classified as *undecided*. We further classify *undecided* grids into two subclasses, *undecided with observation* (mostly for textureless objects in stereo) and *undecided without observation* (for the case of unobserved regions), using the number of observations of each grid position.

From the classification results, if both maps says a grid is *free space*, or if one map says *free space* and the other says *undecided with observation*, then the grid is determined to be free in the final map. Otherwise, the grid is determined to be occupied. The resultant free space map is used for the path planning of the mobile robot.

Fig. 4 shows an example movement of our robot. Fig. 5 shows the maps generated after the movement. In the probabilistic maps, brightness indicates the probability of each grid being occupied by an obstacle. The maps are drawn in the robot coordinates. The table in front of the robot was correctly recognized by the stereo, while the LRF detected only its legs. On the other hand, the recognition by the stereo of the region near the door on the right failed at many positions because features are scarce on the door, while the LRF correctly recognized the region. In spite of recognition failures by one of the sensors at several positions, the integrated map reasonably represents the free space.

3 Speed Control Using the Distance to Undecided Regions

This section describes a method for determining the robot speed so that the robot does not enter an *undecided region* whose vacancy has not been sufficiently decided.

3.1 Basic strategy

Fig. 6 illustrates an example situation where a robot is entering an occluded region; the vacancy of the occluded region or the region near that occluded one is still undecided. As the robot moves, a free region gradually expands with the accumulation of newly observed data. Due to observation uncertainties, in order to be confident with the vacancy of a grid (or a region), the robot needs to observe it several times.

One motion strategy of the robot is to reach an undecided region at the highest speed and observe there; but this may result in an undesirable sudden acceleration/deceleration. We, therefore, controls the robot speed so that the robot can make an enough number of observations to be confident with the vacancy of the region until it reaches there. We call such a speed a *safe speed* and adopt the strategy of selecting the *fastest safe speed*.

We first define a safety criterion for judging whether a speed is safe. Let N be the necessary number of observations of an undecided region. Also let d be the distance to the region and T be the time for one observation (considered to be constant). Since the robot has to observe at least N times before traveling by distance d, the safety criterion is:

$$\frac{d}{vT} \geq N, \tag{1}$$

where v is the robot speed; speed v is safe if this inequality holds. So the fastest safe speed v_{max} is given by

$$v_{max} = \frac{d}{NT}. \tag{2}$$

The robot moves at v_{max} unless that speed exceeds the robot's maximum speed.

To adopt this speed control method, we need to determine N and d. N is determined by considering the observation and the map uncertainty model; d is calculated from the result of a path planning. The next two subsections will explain how to calculate N and d.

3.2 Determining the Necessary Number of Observations for Obtaining Confidence

To determine the necessary number of observations (N), we examined how the probability of obstacle existence changes as more observations are obtained, using the observation uncertainty models used in the map generation method. A typical case examined is the one where the robot is initially $500\ [cm]$ (which is equal to the maximum observable distance of the stereo) distant from a front object and the robot moves at $50\ [cm/frame]$ while observing the object using stereo. Fig. 7 shows the relationship between the number of observations and the probability $P(E)$ that an object actually exists at grids in front of the object in the case where the initial probability is 0.5 (i.e., completely unknown). In this example, five observations are needed for the robot to be confident with the vacancy of the grids (currently,

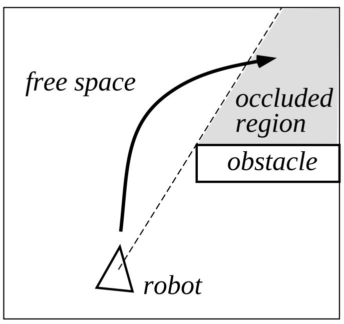


Fig. 6: A robot entering an occluded region.

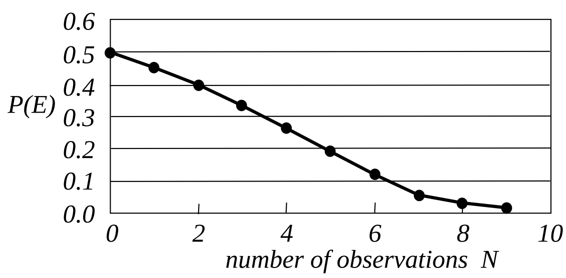


Fig. 7: Decrease of the probability of obstacle existence according to the number of observations.

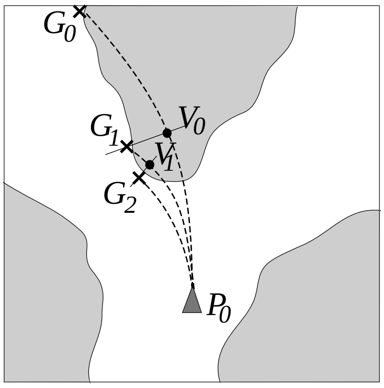


Fig. 8: Find a feasible via point.

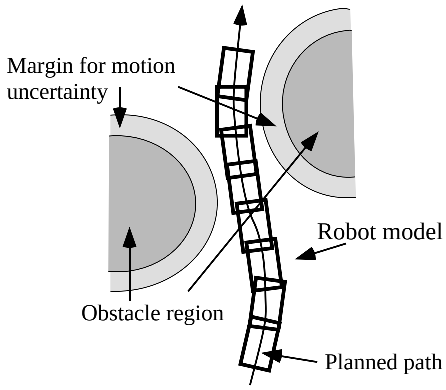


Fig. 9: Safety check of a path.

the threshold for judge the vacancy is 0.2). We examined experimental data to see how many observations are necessary, and found the mean of the necessary number was also about five. So we currently use five as the necessary number of observations, N.

This necessary number is determined based on an optimistic prediction that the front object is always properly observed. If at least one out of five observations fails due to some reason, the state of the grids in front of the object may not be determined as free. Even in such a case, however, the robot can still move safely, because the distance to the undecided region becomes shorter than expected and thus the robot speed is controlled accordingly.

3.3 Determining the Distance to an Undecided Region by Path Planning

The distance d to an undecided region is obtained by planning a safe path in the robot-centered free space map by a heuristic path planner. We currently give the robot a destination in the world coordinates; the robot transforms it to the local coordinates using the estimated robot position. If the destination is in the local map, the robot uses it for path planning. Otherwise, the robot selects a temporary destination for path planning in the current free space which is on the boundary between the free space and an undecided region and is nearest to the given destination. Considering the motion constraint of our robot driven by two powered wheels, we approximately represent a path of the robot by a sequence of circular paths. We use the length of a generated path as the distance d to an undecided region.

Fig. 8 illustrates the process of path planning. The planner searches for a circular path which connects the current robot position and a destination and satisfies the orientation constraint at the current position (arc $P_0V_0G_0$ in the figure). If this path is safe, it is selected. Otherwise, the planner first searches for the point on the circular path which is farthest from the free space (V_0 is selected) and draws a line perpendicular to the tangent line of the circular path there, and selects a temporary destination (G_1) on the line in the free space (V_0). For this temporary destination, the planner repeats the same operation until a safe circular path is found (try arc $P_0V_1G_1$, select G_2, and find P_0G_2). Then this process is iterated with the selected via point (G_2) being the initial position. Currently we limit the maximum iteration of this process to two; in a complex environment, the endpoint of the planned path may not be the given destination. The robot repeatedly plans a new path every time the free space map is updated; each planned path is used for determining the speed and the turning radius of the robot for the current feedback cycle.

In path planning, original obstacle regions are expanded by two types of *margins*: one is for considering the motion uncertainty; the other is for considering the size of the robot. The planner actually verifies the safety of a path by checking collision on points with a certain interval on the path using the robot shape, as shown in Fig. 9. If a collision is detected, the planner goes back to the selection of via points described above.

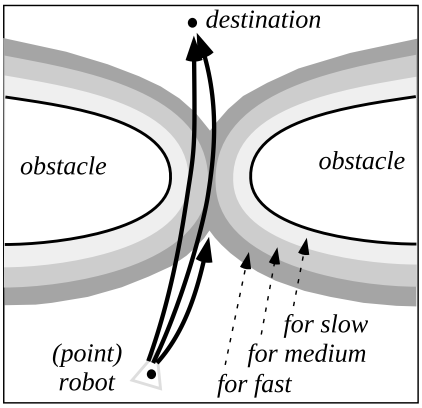


Fig. 10: Path planning for a narrow space with multiple speeds.

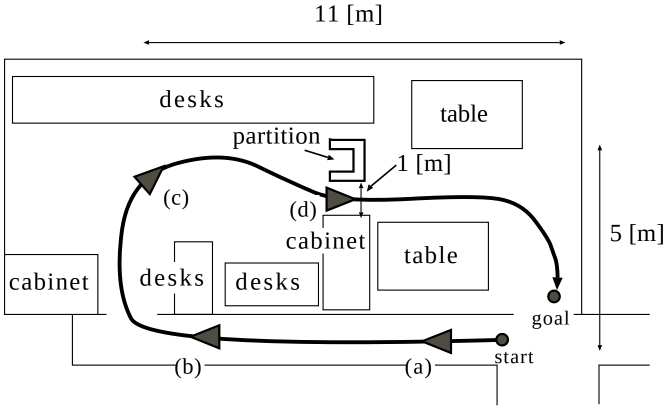


Fig. 11: A navigation experiment.

4 Speed Control Based on the Distance to Obstacles

This section describes a method for determining the robot speed based on the distance to nearby obstacles. Since our previous method [11] was for a completely-known environment and a given trajectory, the collision check was relatively easy. In the current navigation problem, however, since the robot determines not only the speed but also the path to follow, we needs to develop a method for determining both simultaneously.

4.1 Path Planning for Several Robot Speeds

We determine the safety of a speed by judging whether the robot can pass through a narrow space using the speed because we are mainly concerned with speed control in such spaces.

A faster speed results in a larger motion uncertainty (i.e., a larger margin for path planning) and thus may make it impossible for the robot to pass through a narrow space. To find the fastest safe speed, we apply the path planner to the current free space for all of possible robot speeds (i.e., multiple margins for motion uncertainty) and generate the list of planned paths in the ascending order of their lengths. Then we see if there is a gap in the list of the lengths; the existence of such a gap implies that there is a narrow space in front of the robot, and that the robot cannot pass through it at its fastest speed (see Fig. 10). If there is a gap, we divide the path length list into two groups at the gap, and use the path generated by the fastest speed in the longer group. Otherwise, we use the path for the robot's fastest speed. In the case of Fig. 10, for example, the path for speed *medium* is selected. At present, we use a set of five speeds for our robot.

Although a selected path is generated for a speed, the robot may move faster at the first part of the path if the obstacles are distant enough. So we check the collision possibility for faster speeds, and if a faster speed is safe during at least two cycle of visual feedback movement, the highest such speed is selected as the speed for the next cycle. In Fig. 10, for example, the robot may move at the highest speed on the path generated for speed *medium* until it comes near to obstacles.

4.2 Integration of Two Speed Control Methods

The robot simultaneously adopts the two speed control methods. The robot first selects a path and a speed based on the distance to nearby obstacles, and then checks if the selected speed is safe considering the distance to undecided regions. If the selected speed is safe, it is used; otherwise, lower speeds are checked one after another until a safe speed is found.

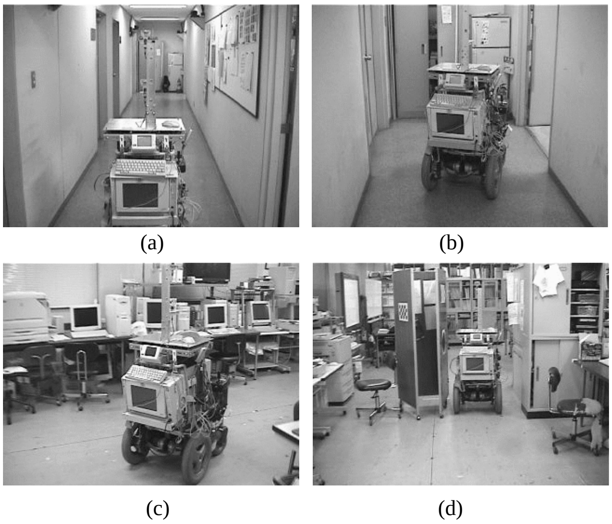


Fig. 12: Snapshots of a navigation experiment.

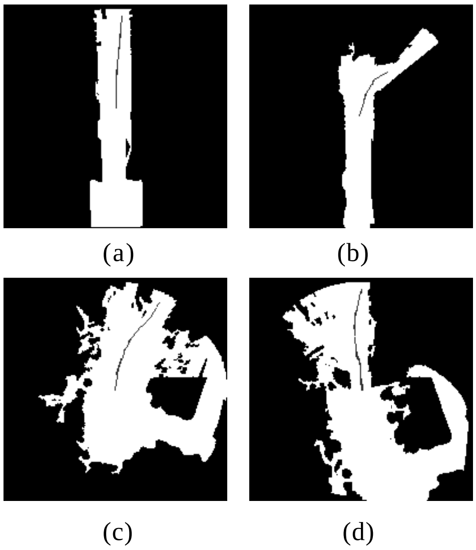


Fig. 13: Free space maps and planned paths.

5 Experimental Results

Fig. 11 illustrates a navigation experiment; the robot moved in a corridor and a room with generating a map and adaptively controlling its speed. The observation cycle is about $0.4\ [sec]$ and the robot's maximum speed is $1.0\ [m/s]$; this is almost the same as the walking speed of an ordinary person.

Fig. 12 shows snapshots of the experiment captured at points (a)-(d) indicated in Fig. 11. Fig. 13 shows generated free space maps and planned paths at the same points. The robot position is at the center of the maps. At point (a), the planned path was long enough to enable the robot to move at its fastest speed. At point (b), since the observed area was limited by a wall (i.e., the distance to an undecided region is short), the robot planned only a short path and slowed down. At point (c), the robot was able to observe a wide area, so it moved fast again. At point (d), although the robot had a view beyond a narrow space between a partition and a cabinet, it slowed down because only the slowest speed was feasible for passing through the narrow space. The total moving distance was about $30\ [m]$ and the total time was about $45\ [sec]$. When the robot moved at the lowest speed, it took about $150\ [sec]$. The proposed speed control method improved the efficiency of navigation about three times with keeping the same safety.

6 Conclusion and Discussions

This paper has proposed a method for controlling the robot speed based on the distance to obstacles and undecided regions. We first defined criteria for judging whether a robot speed is safe. In the case of moving towards an undecided region, we derive the number of observations needed to determine the vacancy of a region with confidence from the sensor uncertainty model; the number is then used with the distance to an undecided region for defining a criterion. In the case of passing through a narrow space, another criterion is defined which uses the results of path planning with several robot speeds. Once the criteria are defined, the robot selects the fastest safe speed. This simple strategy has been shown to be effective in controlling a real mobile robot under uncertainties of observation and motion.

Currently, we treat the reliability of undecided regions uniformly; that is, the necessary number of observations is set to the same for all undecided region, regardless of the number of observations so far. The reliability of each grid should differ from each other, depending on the observation history of the grid. A future work is to consider this factor in determining the necessary number of subsequent observations for each grid.

The current method assumes static environments, where a future situation such as the confidence of the vacancy of a grid (i.e., the probability of obstacle existence at a grid) and the distance to obstacles is sufficiently predictable for speed control. Another future work is to cope with dynamic environments where moving obstacles such as walking persons make such predictions and speed control more difficult.

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