

# Planning of Vision-Based Navigation for a Mobile Robot under Uncertainty

In Hyuk Moon, Jun Miura, Yoshiharu Yanagi, and Yoshiaki Shirai  
Dept. Computer-Controlled Mechanical Systems, Osaka University  
Suita, Osaka 565, Japan

## Abstract

*This paper deals with planning of visual navigation strategies for a mobile robot under uncertainty of both visual data and dead reckoning data. When a robot passes through a narrow space, it has to move slowly while carefully observing surrounding objects and estimating the distances to the objects precisely. On the other hand, the robot can move fast in a widely open space. A novel method is proposed which can adaptively determine the speed of the robot and the visual landmarks, thereby realizing an efficient navigation of the robot. Experimental results show the feasibility of the method.*

## 1 Introduction

Visual information is useful for navigation of mobile robots. If a robot moves only by dead reckoning, the positional uncertainty grows monotonically. Thus, visual information (or information from other external sensors) is utilized to reduce the error for safe and efficient navigation.

Many realtime visual navigation systems have been developed (e.g., [1, 2, 3, 4]). In these systems, a fast image processing and a robot control are iterated in a fixed time cycle. If the time for visual recognition is not negligible, a robot has to be controlled by considering the delay in obtaining a recognition result from the time of image input. In addition, these systems usually deal with situations where precise localization of robot is not necessary. In a cluttered environment, however, a robot often needs precise position control for passing through narrow spaces.

In order to obtain an enough accuracy in localization, much visual information is necessary; this means that a robot needs to get images after every short movement. However such a strategy slows down the robot; it is inefficient to always move slowly. Thus, it is desirable to adaptively change the speed depending on the clutteredness of the nearby environment.

This paper proposes a novel method to plan efficient visual navigation strategies for a mobile robot under uncertainty. By considering the uncertainty of

vision, that of motion, and time for visual recognition, a sequence of viewpoints and visual landmarks (called *reference points* or *RPs*) is generated.

The situation treated in this paper is as follows: a complete (no-uncertainty) map of the environment, the route (a sequence of free spaces that the robot passes through one after another), and the candidates for reference points are given in advance; the mobile robot has a stereo vision system to detect reference points; both vision data and dead reckoning data include uncertainty. The objective of the planner is to generate off-line the navigation strategy which leads the robot to the destination in the minimum time without colliding with obstacles.

## 2 Continuous Motion with Visual Feedback

Since visual processing time is not negligible in usual cases, visual data are obtained with some delay from the image input. By performing a visual processing while the robot is moving, we can integrate visual and dead reckoning data without stopping the robot [5, 6].

Fig. 1 illustrates the relationship between uncertainty estimates obtained in the process of integrating visual and dead reckoning data. In the figure, the uncertainty in a 2-D position, which is represented as an ellipse, is indicated. The order of obtaining uncertainty estimates is also indicated with numbers with circles.

Assuming that the time for processing one image is constant, the interval of viewpoints is determined only by the speed of the robot. For continuously processing images, the robot controls the speed so that it reaches the next planned observation point just at the end of the processing of the current image.

## 3 Basic Planning Strategy

### 3.1 Determining Interval of Viewpoints

When a mobile robot follows a given trajectory with visual feedback, it always deviates to some extent from

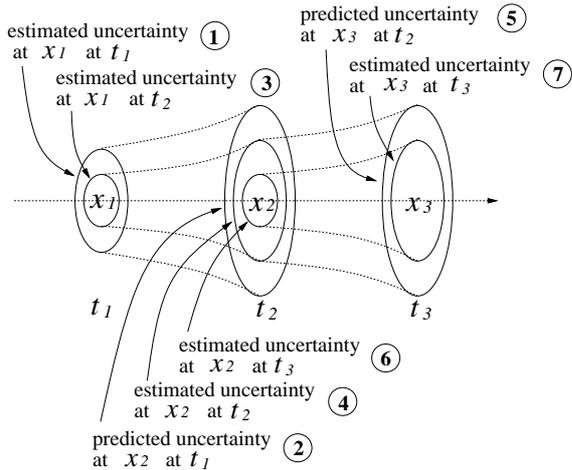


Fig. 1: Uncertainty estimates in non-stop movement.

the planned trajectory because of the uncertainty of motion and vision. If the space around the robot is widely open, the robot can safely recover to the trajectory even in case of a large deviation. If the space is cluttered, however, only a small deviation is allowed. Thus, the allowable positional uncertainty of the robot depends on the clutteredness of the space around the robot. We formulate this dependency to determine an appropriate interval of viewpoints.

We use a three-wheeled mobile robot moving on a 2-D flat floor. The configuration of the robot position is specified by a 3-D vector, whose elements are the 2-D position of the front wheel and the orientation of the robot. The orientation is that of the line connecting the front wheel and the midpoint of the rear wheels. Hereafter we use the word *position* to refer to a configuration. The positional uncertainty of the robot is represented by a probabilistic distribution in the 3-D vector space.

To explain our strategy for determining viewpoint intervals, we define the *worst position*. The worst position at some time point is the position among possible ones which has the largest distance to the trajectory<sup>1</sup> (see Fig. 2). We assume that, if the robot can recover to the trajectory from the worst position, it can also recover from any other possible positions.

Using the notion of the worst position, we choose viewpoints as follows. Let us consider Fig. 1. Suppose that the robot starts following the trajectory at position  $\mathbf{x}_1$  and moves towards position  $\mathbf{x}_2$ . At time  $t_1$ , we can predict the uncertainty at  $\mathbf{x}_2$  (2 in Fig. 1). If the robot can recover from the worst position at  $\mathbf{x}_2$ , this movement from  $\mathbf{x}_1$  to  $\mathbf{x}_2$  is safe. We would like to minimize the total time to reach the destination as long

<sup>1</sup> Although this position may not be the true worst point, we use this position as an approximation.

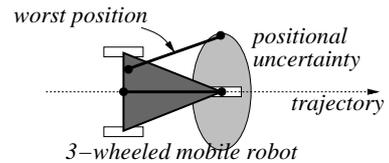


Fig. 2: Worst position.

as no collision occurs. Thus, we choose as the next viewpoint ( $\mathbf{x}_2$ ) the farthest position from whose worst position the robot can recover to the trajectory without collision. The planner repeatedly selects the next viewpoints using the the latest estimate of uncertainty at the current position.

The planner generates a plan before the robot actually moves. Thus, it is necessary to predict the positional uncertainty at each position; this entails prediction of the observation result. As a predicted observation result (observed position of reference points), we use the one which will be obtained at the mean position of the positional distribution. This is based on the assumption that the positional deviation from the planned trajectory is small enough. Using such a predicted observation result, we can calculate the estimates of the robot position and its uncertainty at each position.

### 3.2 Trajectory Generation and Collision Detection

A trajectory is represented by the movement of the midpoint of the rear wheels, and is generated by considering the robot size and the possible deviation of the robot from the trajectory in vision-based trajectory following control.

The size of the robot is considered by setting a margin around each obstacle and by modeling the robot as a line connecting the front wheel and the midpoint of the rear wheels. The size of the margin is set to the half of the robot width plus some predetermined value. If the line touches an enlarged obstacle (or, an *obstacle region*), the robot is considered to collide with the obstacle. The maximum deviation, called the *safety margin*, is the deviation during the robot moves at its highest speed and is estimated from the models of the motion and the vision uncertainty.

Using the obstacle region and the safety margin, a trajectory is generated as follows (see Fig. 3). If a part of the route is covered by an enlarged obstacle region, that part is classified as a *narrow space*; otherwise, the part is *open*. In a narrow space, the robot moves so that the distances to the obstacles on both sides are roughly equal. In an open space, the robot moves on the minimum-length trajectory with consideration of the safety margin. Trajectories are composed of

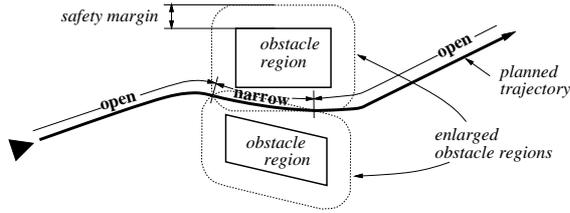


Fig. 3: Outline of trajectory generation.

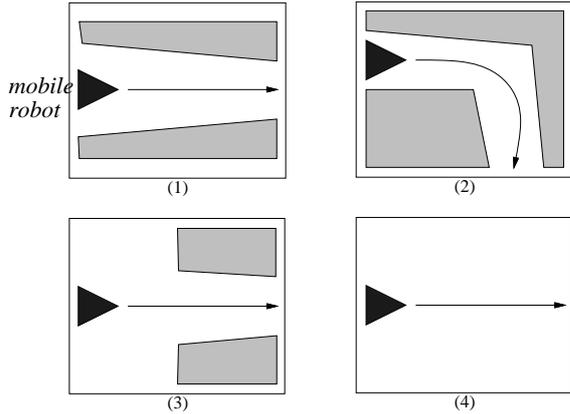


Fig. 4: Four categories: (1) straight movement between obstacles; (2) curved movement between obstacles; (3) entering a narrow space; (4) movement in an open space.

straight-line and circular segments. Segments are connected smoothly.

## 4 Planning Procedures

We classify the possible situation into the following four categories (see Fig. 4) and prepare a planning procedure for each category:

- (1) straight movement between obstacles,
- (2) curved movement between obstacles,
- (3) entering a narrow space, and
- (4) movement in an open space.

### 4.1 Straight Movement between Obstacles

In this case, the trajectory is set so that the distances to obstacles on both sides are equal. When the robot's front wheel touches the obstacle region, the robot can recover to the trajectory by steering to the opposite direction to the obstacle (see Fig. 5). Thus, the next viewpoint is set at the position where the worst position first touches the obstacle regions. For this movement, two reference points (RPs), one from each side, are selected which are observable (even at the worst position) and the nearest to the robot.

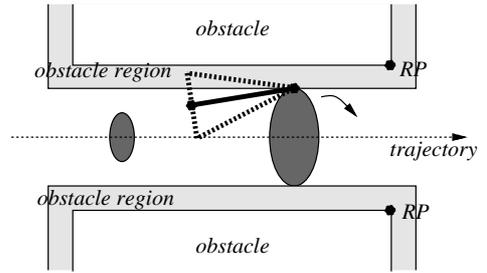


Fig. 5: Straight movement between obstacles.

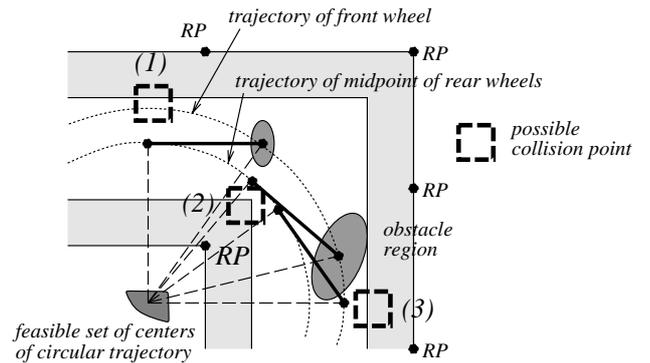


Fig. 6: Curved movement between obstacles.

### 4.2 Curved Movement between Obstacles

When the robot moves on a curved trajectory among obstacles, there are three possible collision points (see Fig. 6): (1) collision of the front wheel with the outer obstacle when the robot enters the curved trajectory; (2) collision of a rear wheel with the inner obstacle while the robot is turning; (3) collision of the front wheel with the outer obstacle when the robot exits from the curved trajectory.

We use a single circular trajectory when the robot changes its orientation; the radius of the circle is determined empirically from the distance between the inner and the outer obstacles. For each possible collision point mentioned above, we can calculate a set of the centers of the circular trajectory for which the robot does not collide at that point. Then, the feasible (no-collision) set of centers is calculated as the intersection of three such sets. The triangle-like region in Fig. 6 indicates the set. The center of mass of the set is selected as the center of the circular trajectory.

On a circular trajectory, the next viewpoint is determined at the position where the worst position of the robot first touches an obstacle region. When the robot enters the curved trajectory or exits from the trajectory, two reference points, one from the innermost point of the inner obstacle and the other from the

outer obstacle, are selected. During the movement on the trajectory, two reference points are selected from the outer obstacle which are observable and the nearest to the robot.

The movement of entering the curved trajectory is treated as the entering movement (see Sec. 4.3) into a narrow space whose width is equal to that of the region of possible circle centers in the direction perpendicular to the robot movement.

### 4.3 Entering Narrow Space

When the robot enters from an open space into a narrow space, we consider the following two conditions: (1) the front wheel can enter the narrow space; (2) when entering the narrow space, the angle between the trajectory and the robot orientation is less than a certain value, which depends on the width of the narrow space, so that the robot can safely recover to the trajectory in the narrow space.

These conditions are illustrated in Fig. 7. We consider two circles drawn by the midpoint of the rear wheels: one, which is indicated by the left smaller circle in the figure, is drawn when the robot proceeds with the maximum steering angle from the worst position; the other, which is indicated by the right smaller circle in the figure, is drawn when the robot enters the narrow space with the maximum steering angle and with the maximum allowable orientation of the robot. If we can draw a tangent line between these circles, the robot is considered to be able to enter the space.

The farthest point at which the above entering conditions are satisfied is selected as the next viewpoints. The reference points used are the inner-most points of the two obstacles forming the entrance of the narrow space.

### 4.4 Movement in Open Space

For the movement in an open space, the farthest point the robot can reach during one cycle of visual data

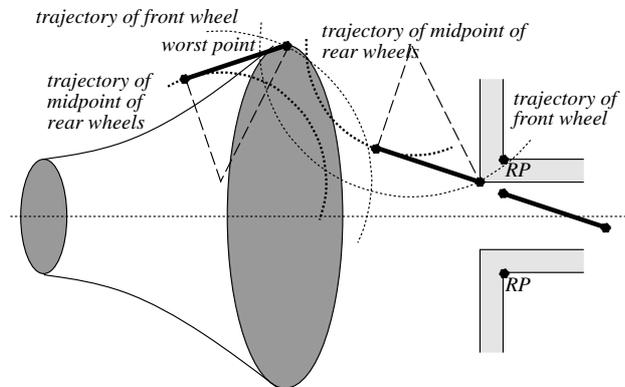


Fig. 7: Entering a narrow space.

processing is selected as the next viewpoint. Two reference points are selected which are observable and the nearest to the robot.

## 5 Position Estimation of the Robot

The robot estimates its position using both dead reckoning data and visual data. In dead reckoning, the movement of the robot is estimated from the steering input and the odometer reading. These two values are considered to be the sources of uncertainty in the dead reckoning data. In visual recognition, the robot uses a stereo vision system, in which the uncertainty caused by the quantization error is considered [7].

The above measurements with errors are integrated into the estimate of the robot position by using the Extended Kalman Filter [8].

## 6 Image Processing for Detecting Reference Points

We suppose that the robot is in a typical office environment. Since there are many artificial objects which have vertical straight segments, we use such vertical segments as reference points. If a group of vertical segments coexists in a small scene region, as in the case of thin objects such as the leg of a table, we use such a group as a single reference point.

Since the robot has the estimate of its positional uncertainty, it can predict the possible 3-D *scene* region within which a reference point exists. This region information can be backprojected onto the stereo images to limit the possible *image* region within which the edge segments corresponding to the reference point exists.

Then, vertical edge segments are extracted in that image region in the left and the right image. After extracting and grouping segments, we search for possible matches between images. For each segment in the left image, corresponding segments in the right image are detected based on the epipolar and the similarity constraint; a pair of segment can be matched if their vertical positions overlap each other to a certain extent and they have similar directions and contrast values. From the matched pair of segments, the candidates of reference points are obtained.

If there are still multiple candidates of reference points after matching between images, we further use the constraint on the relative displacement in the *scene* between reference points to disambiguate them among the possible candidates.

Fig. 8 shows an example of reference point extraction. This image was taken during the entering movement (see Section 4.3). In the figure, the possible image region and the detected pairs of vertical segments

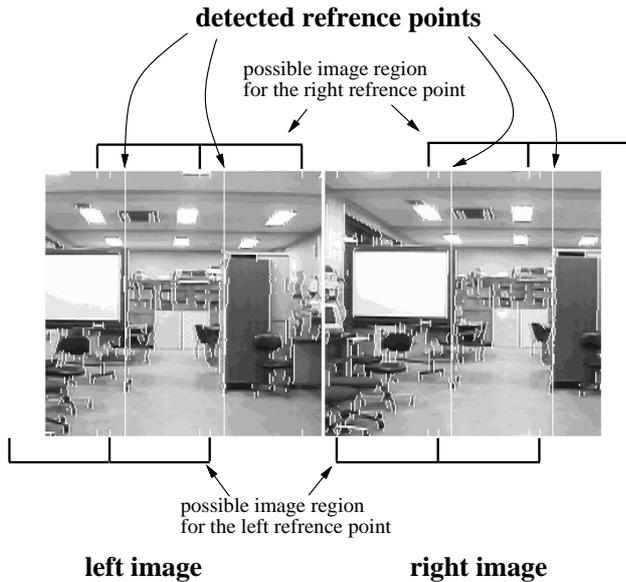


Fig. 8: Detection of reference points.

for the two planned reference point are indicated.

Although our stereo matching method is relatively simple, it performs well in most cases because only a small number of candidate segments are extracted using the position information and the map.

## 7 Experimental Result

We conducted experiments using a real mobile robot in our laboratory. The route given to the robot is composed of a sequence of the following movements: (1) movement in an open region; (2) movement to enter a narrow region; (3) movement between obstacles (straight); (4) movement between obstacles (curved). Fig. 9 shows the map of the environment and the planned viewpoints and reference points. Small ellipses indicate the planned viewpoints and the predicted uncertainty at those positions. Small filled circles indicate the planned reference points.

At each viewpoint, the robot obtains the current position estimate. Using the estimate, the robot calculates the positional deviation from the planned trajectory, and then generates a recovery trajectory. Currently the recovery trajectory is simply generated to lead the robot towards the next planned viewpoint on a single circular trajectory.

Fig. 10 shows the result of a trial. In the figure, the actual movement of the robot, the predicted uncertainty, and the estimated uncertainty are indicated. In this trial, the robot succeeded in entering the curved trajectory starting at the side of the tables. Fig. 11 shows the sequence of the left images and the extracted reference points. Fig. 12 is the snapshots of the trial.

## 8 Conclusions and Discussion

We have proposed a method to plan efficient navigation strategies for a mobile robot under uncertainty. By considering both the predicted positional uncertainty and the configuration of obstacles, the interval of viewpoints, which is equivalent to the speed of the robot in our case, is adaptively determined according to the clutteredness of the nearby environment. Experiments using a real mobile robot show the feasibility of the method.

The planner currently selects two reference points at each position by only considering their visibility and distance from the robot. Using more reference points and/or considering other factors such as the detectability of reference points would enhance the robustness of the robot localization.

Another future work is to use the active mechanisms of the stereo camera head. Currently the camera direction is fixed to direct forward. By using these mechanisms, the robot will select reference points more flexibly among those which exist in various directions.

## References

- [1] E.D. Dickmanns and A. Zapp. Autonomous High Speed Road Vehicle Guidance by Computer Vision. In *Automatic Control - World Congress*, pp. 221-226. 1987.
- [2] V. Graefe and K.-D. Kuhnert. Towards a Vision Based Robot with a Driver's License. In *Proceedings of the 1988 IEEE Int. Workshop on Intelligent Robots and Systems*, pp. 627-632, 1988.
- [3] L.S. Davis. Visual Navigation at the University of Maryland. *Robotics and Autonomous Systems*, Vol. 7, pp. 99-111, 1991.
- [4] D. Pomerleau. *Neural Network Perception for Mobile Robot Guidance*. Kluwer, 1993.
- [5] A. Kosaka, M. Meng, and A.C. Kak. Vision-Guided Mobile Robot Navigation using Retroactive Updating of Position Uncertainty. In *Proceedings of the 1993 IEEE Int. Conf. on Robotics and Automation*, pp. 2: 1-7, 1993.
- [6] S. Maeyama, A. Ohya, and S. Yuta. Non-Stop Outdoor Navigation of a Mobile Robot. In *Proceedings of the 1995 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pp. 130-135, 1995.
- [7] J. Miura and Y. Shirai. An Uncertainty Model of Stereo Vision and Its Application to Vision-Motion Planning of Robot. In *Proceedings of the 13th Int. Joint Conf. on Artificial Intelligence*, pp. 1618-1623, Chambéry, France, August 1993.
- [8] N. Ayache and O.D. Faugeras. Maintaining Representations of the Environment of a Mobile Robot. *IEEE Trans. on Robotics and Automat.*, Vol. RA-5, No. 6, pp. 804-819, 1989.

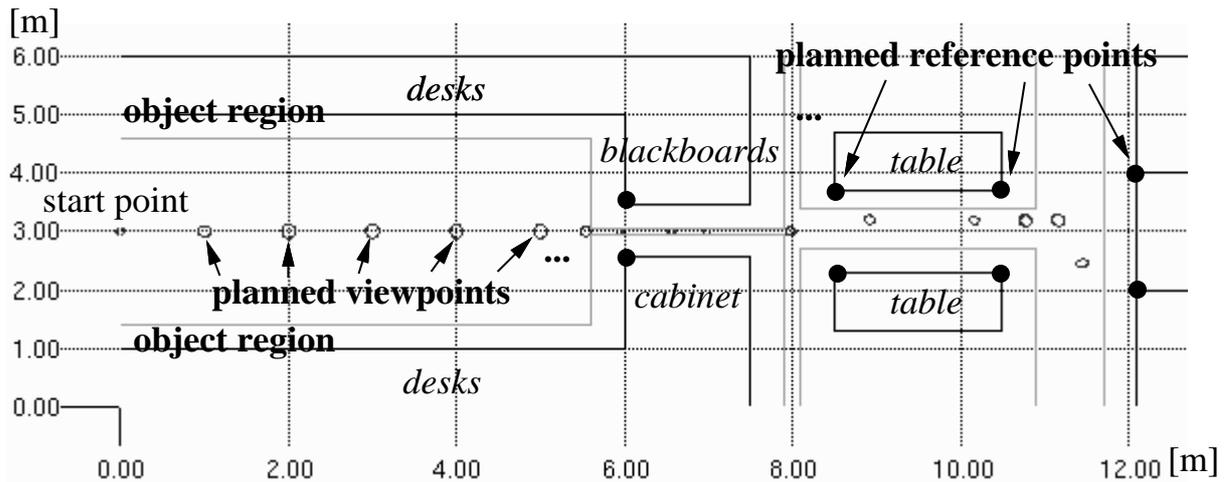


Fig. 9: Map of the environment and generated plan.

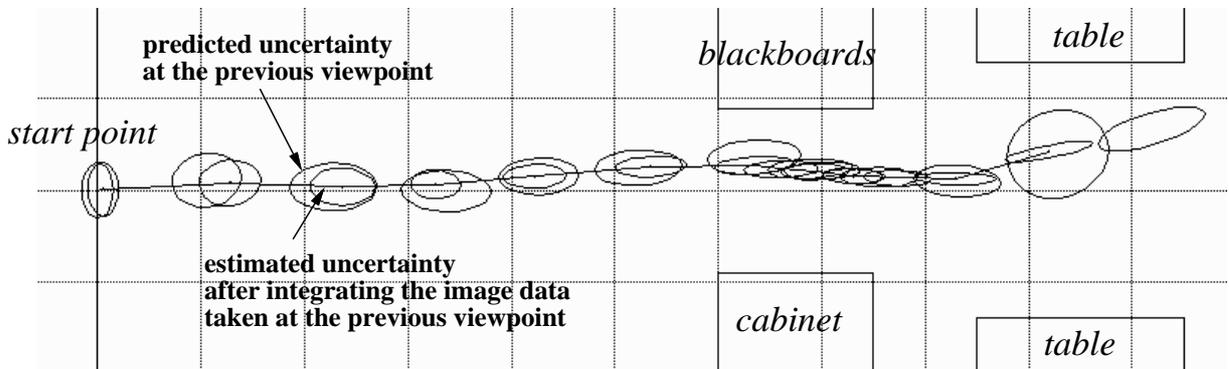


Fig. 10: Experimental results. The scales for  $x$  and  $y$  axes are different.

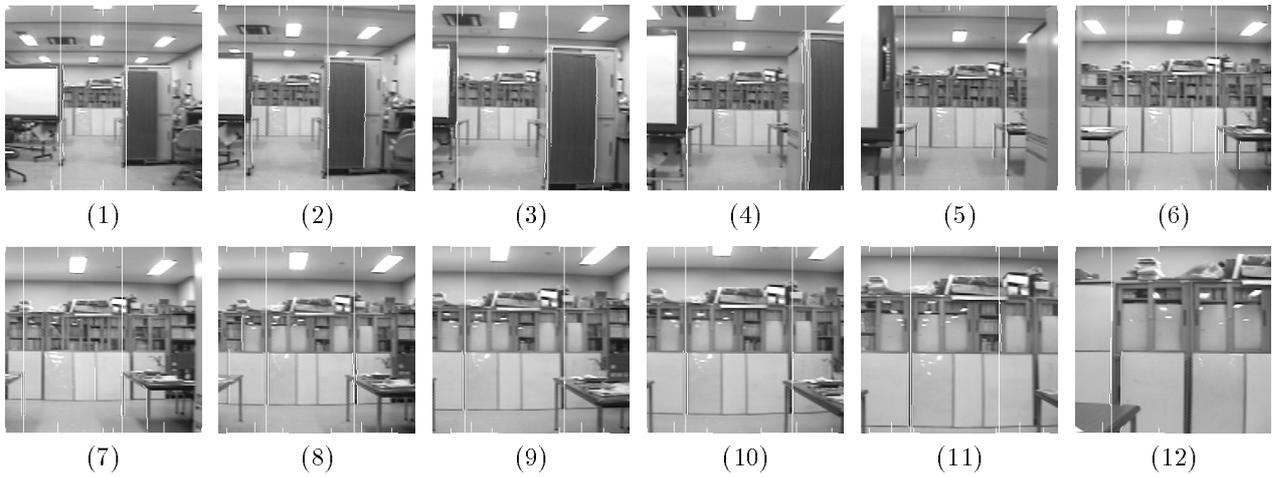


Fig. 11: Sequence of images and extracted reference points.



Fig. 12: Snapshots of the mobile robot moving with the planned visual navigation strategy.