Robots Find a Better Way: A Learning Method for Mobile Robot Navigation in Partially Unknown Environments*

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Abstract. This paper represents a method for mobile robot navigation in environments where obstacles are partially unknown. The method uses a path selection mechanism that creates innovative paths through the unknown environment and learns to use routes that are more reliable. This approach is implemented on Khepera robot and verified against shortest path following by wave transform algorithms. Based on the experimental data, we claim that robot's trajectory planned by wave transform algorithms is difficult to predict and control unless the environment is completely modelled and the localisation errors are small. We show that even small unmodelled obstacles can cause large deviation from the preplanned path. Our complementary approach of path selection decreases the risk of path following and increases the predictability of robot's behaviour.

Introduction

Mobile robots in human inhabited environments are expected to navigate safely and reliably as well as minimize travel time and energy consumption. Since real-world environments are complex, often unstructured and dynamic, it is impossible to build a complete model of robot's surrounding and keep it up to date. The robot is thus expected to operate as efficiently as possible with a rather limited amount of information.

Until now, research in mobile robot path planning has focused on finding optimal routes from start to goal. The optimality is usually measured in terms of travelled distances [1]. Other measures are also used, e.g. confidence value [2]. For planetary rovers the efficiency of a path is often expressed in terms of slope or roughness of the surface [3, 4].

Robots use local replanning to avoid unexpected obstacles in partially unknown environments. Since local planners do not use global knowledge, the behaviour of the robot is not globally optimised. Salich and Moreno have referred to this problem as to the dilemma of authority vs. freedom [5]. The dilemma rises from the fact that classic planners produce rigid orders while the behaviour of local reactive planners is unpredictable. Some researchers try to overcome this problem by incorporating global information to local decision making [6, 7].

Path planning algorithms used in robotics have been proven to give a globally optimal solution in globally known static environments. Their efficiency is not investigated in

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complex, dynamic and partially unknown environments during long periods of time. Our experimental data suggests, that the dilemma local vs. global decision making is not so important as it is anticipated e.g. in [8]. It rather appears that if the global planner does not have all the global information about the environment. It anyway fails to create globally optimal plans.

Based on our experimental data we conclude that the environment has a much more significant effect on the behaviour of the robot than the algorithm used. Even if the robot always replans globally and always uses all the global knowledge available, it has a minor effect on the total outcome unless the environment is completely modelled. Our tests also show that robot's trajectory is difficult to predict and control. Even small unmodelled obstacles can considerably deviate the robot away from its globally planned path.

A good characteristic of a learning system is the predictability of its behaviour. The systems that better predict the outcome have learned the environment better. A mobile robot can predict its behaviour when it knows its position with a great certainty after a certain period of time. The ability to predict the trajectory makes it possible to optimise other parameters like travel time or energy consumption.

The problem we try to solve is thus how to optimise the behaviour of the robot in a partially unknown environment during a long period of time. There are two complementary approaches to increase the predictability of robot's behaviour. It is possible to gather more information about the environment to plan optimal paths. But since our experiments show that even small imprecision in input data or noise can considerably affect the robots trajectory, we have chosen an opposite approach. Instead of trying to model the environment we look for trajectories in a partially unmodelled environment that can be followed with a great precision.

We propose a method of covering a rectangular grid-based map with sub-optimal paths. Previously we have described the method in detail [9] and have proven that the number of possible trajectories grows linearly with a small constant when the size of the map is increased. Therefore the method we describe can be used even in large-scale environments. The robot will then try to follow these paths and memorise them until it finds a trajectory that is sufficiently stable and easy to follow.

In our previous work [10], we have tested or approach in a totally unknown changing environment. The results show that the robot is able to adapt to the changes when the unknown obstacles are frequently replaced and learns to use trajectories that take it safer to the goal.

In this paper we report a series of tests to investigate the robot's behaviour in partially known environments. The environment is static to show the cause-effect relationship between the model of the environment and the robots behaviour. It allows us to draw a conclusion that the behaviour is influenced by the environmental model and the path planning algorithm but not by the robot's ability (or inability) to adapt to the changes.

Our paths selection algorithm is verified against shortest path following by a wave transform algorithm of [11] with global replanning.

Our initial hypothesis was that the shortest path following with global replanning would soon outperform our method when the environment becomes better known and when the unknown obstacles are smaller. We guessed that the shortest path planner would find the optimal path more likely if it knows the environment better. Tests did not confirm that hypothesis. On the contrary, the experimental data shows that wave transform algorithms are very sensitive to small imprecision in an environmental model. Even small unknown obstacles (or possibly sensor noise) can cause large deviation from the originally planned path.

Our method of path selection has two limits. First, it assumes that the robot will repeatedly traverse between two entry points. This assumption makes it possible to try several alternative trajectories. Fortunately there are plenty of mobile robot applications (e.g. transportation, surveillance, convoying) that presume repeated traversal between specified target points.

Second, the robot needs a fairly precise positioning system to follow the trajectories it has planned. In our tests we use an overhead camera to determine the robot's pose. We therefore suggest that the method works equally well with a satellite or pseudolite-based navigation. Since we test our approach in an environment where some static obstacles are modelled, it is principally possible to use these objects as landmarks. Yet we do not have any experience on how the robot would behave when the localisation errors are large, like it often happens with landmark based navigation.

In the next section we form the problem and list the assumptions we have made. We then describe briefly our path selection mechanism. After that, we describe the experiments and draw conclusions based on the experimental data.

1. Problem statement

It is further assumed that:

1. The environment is dynamic and large. It is not possible or feasible to model it precisely and/or keep the model constantly updated.
2. The environment contains obstacles with unknown size and location. Traversing this environment implies risk of colliding with these obstacles, being delayed when manoeuvring around them or ending up in a deadlock.
3. Sensorial capabilities of the robot are insufficient to distinguish between static, dynamic and semi-dynamic obstacles (e.g. between pillars and people, steady and replaced furniture).
4. Mapping, path planning and localisation are not the main objectives of the robot. These are presumptions to make the successful completion of a mission possible. Therefore they cannot take all of time and the computational recourses. Some resources are also needed for the main task that should be fulfilled as fast and safely as possible.
5. Localisation errors are small and do not accumulate and therefore it is possible to follow a preplanned path rather precisely.

The assumptions 1 and 3 seem to contradict with the experimental design where the environment is actually kept static. However, a static environment is not the necessary precondition of the approach. The environment is kept static only to find out the causal relation between an environmental model and the behaviour of the robot.

The problem we aim at solving is the following: find reliable paths between previously determined target points so that following them minimises collision risk and speeds up the mission.

Our approach to the problem solving is based on the following observation: in a dynamic environment with an unknown obstacle distribution, the best path to the goal is not necessarily the shortest. Depending on the nature of the environment, there may exist routes that are longer but easier to follow in terms of time or safety. By introducing a path generation algorithm, the robot can test several alternatives to reach the goal. By remembering its path following experiences, it can learn to follow paths that save time and reduce risk. As the environment changes, the robot will re-evaluate its experience and will adapt to use new easily traversable paths.

2. Path selection

Theoretically the number of different paths on a grid-based map is overwhelming. There are too many alternatives to travel between two points and the robot could never try all of them. In addition, most of those paths are unfeasibly long, crooked and difficult to follow. So the aim of the path selection algorithm is to:

- generate paths that are easy to follow if free from obstacles;
- generate paths that are as much as possible different from each other to let the robot find out as many innovative solutions as possible;
- provide a mechanism that in practice is able to discover virtually all possible alternatives;
- cover whole space of innovative solutions with as few alternatives as possible in order to maintain the robot's ability to generalise and keep the memory constrained.

We propose a method that works by dividing the grid into paths segments and then generating paths that cover all these segments. The full description of the method and its formal analysis is presented in [8].

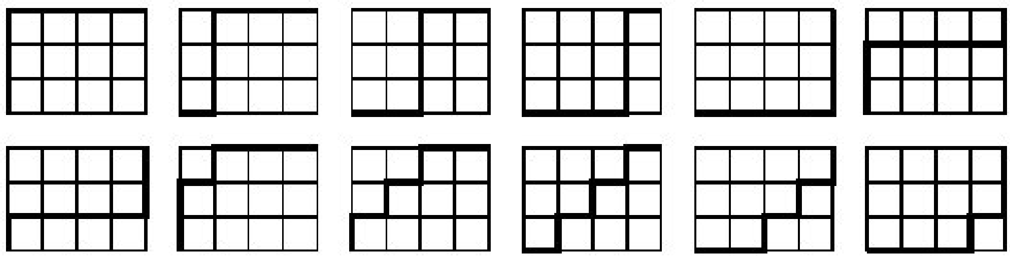

Figure 1: The cover of a 3 × 4 grid.

The paths selected by the robot are limited to those not having back turns and covering all the grid segments of length 2. Theoretically there are $2^{(m-1)(n-2)+(m-2)(n-1)}$ possible ways to cover a m × n grid with such a minimal cover. Figure 1 shows one possible cover of a 3 × 4 grid. In practice, paths relaxation is used to smoothen the paths and the zig-zags will be straightened.

It is proven in [8] that for a grid of the size m × n, the cardinality of the minimal cover is 2m+2n-2 paths. It means that the number of different paths is very small and grows linearly with a small constant, which makes it well scalable for very large domains.

3. Experimental Design

The experiments are conducted using a mini-robot Khepera. It is a differential drive miniature circular robot (with radius 26 mm) equipped with IR sensors for collision avoidance and it can be connected to a PC over a serial link.

The localisation system is presented in Figure 2. A video camera is mounted to the ceiling to recognise the position and orientation of the robot. The PC processes the camera image to find robot's position and a computer algorithm controls the robot over a serial link. In this way the localisation errors are rather small (usually comparable to the size of the robot).

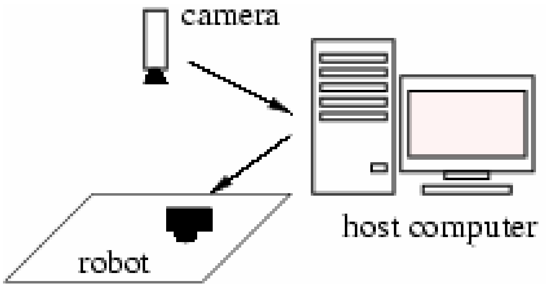

Figure 2. Localisation system.

The size of our test environment is 1860 mm × 1390 mm. It is represented in Figure 3 to the left. The picture in the middle represents the same environment as shown from the overview camera. The picture to the right in Figure 3 is the graphical interface of the computer program that controls the robot and monitors its behaviour.

Figure 3. The test environment (to the left), the same environment seen through the overview camera (in the middle) and as modelled by the control program (to the right).

The robot traverses repeatedly between the lower left corner and upper right corner of the environment in Figure 3. The physical environment for all test runs is the same but the environmental model varies. Figure 4 represents 3 different maps that are used to determine how much the environmental model affects the results.

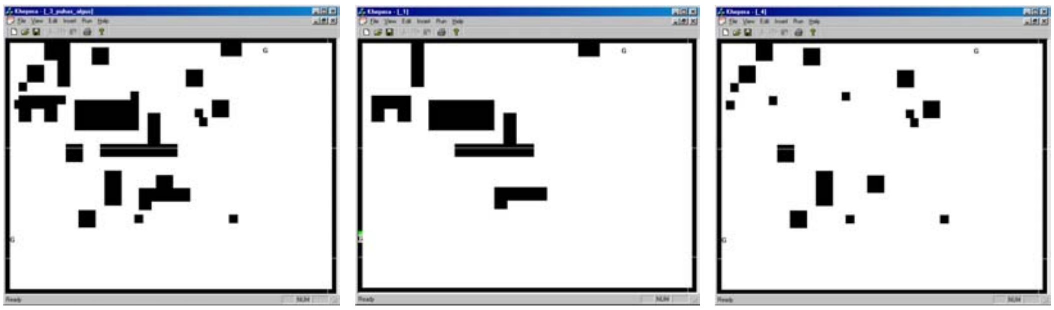

Figure 4. Environmental models used in experiments: a fully known environment (to the left), environment with large obstacles modelled (in the middle) and with small obstacles modelled (to the right).

The map to the left of Figure 4 is the precise model of the environment, containing the precise location of all obstacles. The map in the middle models only large obstacles while the location of small obstacles in unknown. The map to the right models only small obstacles while the large obstacles are unknown.

We compare our path selection method to shortest path following by a wave transform algorithm[10] with global replanning. Table 1 shows the number of trials with every environmental model with both path planning algorithms, shortest path planning vs. path selection. The number of trials depends on how fast the process stabilises.

Table 1. Number of trials.

Environmental model	Nr. of trials	
	Path selection	Shortest path
1.All obstacles known		10
2.Large obstacles known	20	50
3.Small obstacles known	20	50

The efficiency of the path planning algorithm is characterised by four parameters: number of replannings, travel time, travel distance and deviation from the originally pre-planned path.

One trial means planning a path from the lower left corner of the test environment to the upper right corner (or back again), following this path, replanning when an unknown obstacle is detected and recording the data when the robot reaches the goal.

The shortest path planning algorithm is the following:

1. Plan off-line a path from current start to current goal. This path is the shortest path to the goal calculated by a distance transform method [10].
2. Follow the path.
3. If an obstacle is detected plan a new path from its current position to the goal by a distance transform algorithm.
4. Repeat steps 2 and 3 until goal is reached.
5. Record travel time, travel distance, number of obstacles detected and deviation from the path planned at step 1.

The path selection algorithm is the following:

1. At the first trial select a sub-optimal path planned by the method described in Section 3.
2. Follow the path.
3. If an obstacle is detected plan a new path from its current position to the goal by a distance transform algorithm.
4. Repeat steps 2 and 3 until goal is reached.
5. Smoothen the actually followed path to remove cycles, zig-zags and gaps caused by localisation errors.
6. Store the smoothened path together with the travel time, distance, number of replannings and deviation.
7. At next trial check if there is a stored path with acceptably low number of replannings. If yes, follow this path. If no, choose a new path by using a method described in Section 3.
8. Repeat steps 2 to 7.

4. Experimental Results

All data from experiments, including recorded parameters at every trial, snapshots of every followed path and code of the control program are available at http://math.ut.ee/~kristo/khepera/. We here represent only some general statistics to compare the path planning strategies described above.

Table 2 represents data on the shortest path planning experiment. Table 3 represents data on path planning with path selection.

The efficiency of the path selection mechanism in case of a small number of trials largely depends on how fast the robot finds a sub-optimal path that is easy to follow. While running the test in the 3rd environment (with small obstacles known) the robot found an easy-to-follow sub-optimal path at the first trial. For the sake of an unbiased interpretation we also represent data of another experiment that shows the worst case we have encountered. The robot had to try 4 sub-optimal paths before it found one that was good enough. The last row of Table 3 therefore gives two figures for every parameter, the best result vs. the worst result.

Table 2. Results of shortest path planning

Environmental model	Nr. of replannings	Travel time	Travel distance	Deviation from the preplanned path
1.All obstacles known	0.3	104	2555.0	43.8
2.Large obstacles known	12.7	123.3	2697.3	114.7
3.Small obstacles known	14.8	134.3	2768.0	107.0

Table 3. Results of planning with path selection

Environmental model	Nr. of replannings	Travel time	Travel distance	Deviation from the preplanned path
1.All obstacles known				
2.Large obstacles known	0	104.1	2584.6	29.2
3.Small obstacles known	0/5.7	129.8/123.5	2534.2/2805.5	29.2/145.0

5. Discussion and conclusions

The first trials test the shortest path following strategy in a completely known environment (the first row in Table 2). It is the ideal case where globally best paths are planned with all available information. A closer look to the statistical data (available at the website) shows that the behaviour of the robot is predictable and stable. It means that we are able to control the robot with the great precision. Localisation errors, imprecision of mechanical linkages and sensor noise have no significant effect to the test results. Keeping all other things equal and changing only the environmental model or the path planning algorithm we can claim that the changes in experimental results are caused by one of the latter reasons.

Next we have verified the behaviour of the robot using two path planning strategies. Speaking in terms of decision-making theory, in case of shortest path planning, the robot can be described as a rational utility maximising agent. It always tries to find the shortest path to the goal considering all information available. In the case of path selection, the robot can be described as an explorative agent. It randomly tries sub-optimal solutions to escape the local minimum and find a globally best solution.

The results show that by and all, the explorative agent is more successful. The advantage is apparent despite that the number of trials with the path selection method is smaller than the number of trials with the shortest path algorithm. Since the environment is static, larger number of trials would simply increase the advantages of the path selection mechanism since the robot would use the already found good solutions. At the same time the robot using the shortest path planning strategy does not learn and its behaviour never stabilises.

Another conclusion is that as soon as the environment is not modelled completely, the trajectory of the robot is hard to predict and control. Table 2 shows that small obstacles can cause large deviation than large ones. The path selection algorithm represented here is one possibility to find reliable trajectories that increase the predictability of robot's behaviour.

Finally, we conclude that shortest path planning is not a relevant problem in partially unknown environments. As soon as the robot does not have all global knowledge available, sub-optimal solutions give at least as good results as the optimal one. In order to increase the reliability of mobile robot applications, much more importance should be paid on modelling the environment and its changes.

This study obviously raises a question of how well the test environment models a real large-scale dynamic environment and how much Khepera can be considered as a model of a real robot. We suggest that the first question can be answered positively since this study focuses rather on modelling than navigation. We therefore expect the main conclusion that the environmental model plays a more important role than the path planning strategy, to hold also in real-world applications. However, we cannot be certain how much this conclusion can be extended to nonholonomic robots that due to their kinematics are not able to follow any possible pre-planned trajectory.

References

[1] A.Yahja, S.Singh, A.Stentz, "An Efficient on-line Path Planner for Outdoor Mobile Robots". *Robotics and Autonomous Systems*, 32, pp. 129-143, Elsevier Science, 2000.

[2] U.Nehmzow, C.Owen, "Robot Navigation in the Real World: Experiments with Manchester's Forty Two in Unmodified Large Environments", *Robotics and Autonomous Systems,* 33, pp.223-242, Elsevier Science, 2000

[3] A. Howard, H.Seraji, "Vision-Based Terrain Characterization and Traversability Assessment", *Journal of Robotic Systems*, Vol. 18, No.10, pp. 577-587, Wiley periodicals, 2001.

[4] D.B.Gennery, "Traversability Analysis and Path Planning for Planetary Rovers", *Autonomous Robots*, Vol. 6. pp. 131-146, Kluwer, Academic Publishers, 1999..

[5] M.A. Salichs and L. Moreno. "Navigation of Mobile Robots: Open Questions", *Robotica,* Vol. 18, pp. 227-234, Cambridge University Press, 2000.

[6] H.Seraji, "New Traversability Indices and Traversability Grid for Integrated Sensor/Map-Based Navigation", *Journal of Robotic Systems*, Vol. 20, No.3, pp. 121-134, Wiley periodicals, 2003.

[7] A. Sgorbissa, R.Zaccaria, "Roaming Stripes: integrating path planning and reactive navigation in a partially known environment", *11th International Conference on Advanced Robotics - ICAR 2003,* Coimbra, Portugal, July 2003

[8] Robin R. Murphy, Ken Hughes, Alisa Marzilli and Eva Noll, "Integrating explicit path planning with reactive control of mobile robots using Trulla", *Robotics and Autonomous Systems,* Vol. 27, Issue 4, pp. 225-245, Elsevier Science, 1997.

[9] M.Kruusmaa, J.Willemson. "Algorithmic Generation of path Fragment Covers for Mobile Robot Path Planning", *Technical Report*, 2003.

[10] M. Kruusmaa, J.Willemson, K.Heero. "Path Selection for Mobile Robots in Dynamic Environments", *Proc. of the 1st European Conference on Mobile Robots,* pp. 113 - 118., Poland 2003.

[11] A. Zelinsky. "Using Path Transforms to Guide the Search for Findpath in 2D. *The Int. Journal of Robotics Research,* Vol. 3 No. 4, pp. 315-325, August, 1994.