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A Novel Hybrid Algorithm for Robots Paths Planning

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ABSTRACT

Presented article is studying the issue of path navigating for numerous robots. Our presented approach is based on both priority and the robust method for path finding in repetitive dynamic. Presented model can be generally implementable and useable: We do not assume any restriction regarding the quantity of levels of freedom for robots, and robots of diverse kinds can be applied at the same time. We proposed a random method and hill-climbing technique in the area based on precedence plans, which is used to determine a solution to a given trajectory planning problem and to make less the extent of total track. Our method plans trajectories for particular robots in the setting-time scope. We performed sequence of100tests with 8 robots for comparing with coordination method and current performances are effective. However, maximizing the performance is still possible. These performances estimations performed on Windows operating system and 3GHz Intel Pentium IV with and compiles with GCC 3.4. We used our PCGA robot for all experiments. Moreover, this article utilized lookup tables to keep expenses the formerly navigated robots made, increasing the number of robots don't expand computation time.

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1. INTRODUCTION

Track finding is a basic problem in moving robotics. In [1] Latombe acclaimed, the potential of optimal navigating its movement is "notably essential because a robot completed assignment by moving in the real environments."

The issue of harmonizing numerous of movable robots got remarkable consideration in the related approaches to this article. Whenever several robots are deployed in the same environment there is the need for coordinating their movements. Trajectories for the individual robots have to be computed such that collisions between the robots and constant barriers just like between the robots among themselves are prevented. In Especial, in the multi robot configurations various unwelcome statuses can take place, such as congestion's or deadlocks. For instance, let have the occasion with three robots presented in the first Figure. Starting positions for the robots indicated by large circles whereas the small dots correspond to the goal locations. The lines are the individual optimum pathways for the robots. Assuming that the hallways are not wide enough for two robots to cross simultaneously, no path can be found for robot 1; if robot 3 enters the corridor before robot 1 has left it. In that case third robot obstructs the path of first robot. Hence, the robot is not able to attain its designated target, point G_1. This example shows that there is the need of coordinating the motions whenever current schemes for overcoming the problem of movement navigating for more than one robot is categorize to following major classes [2]: the *centralized* and the *decoupled* techniques. In the former method the setting scopes of the particular robots are joined into one compound setting scope and next explored for a track for the entire compound model. Contrary, the later method at the initially, calculates divided tracks for particular robots and then attempts to solve probable collisions of the produced routs. Conflicts are situations in which the robots try to reach the same location simultaneously or in which they would get too close to each other.

In theory, centralized methods are capable to determine the optimum solution to any finding issue while an answer exists; time complexity of these methods is exponential with respect to the directional dimension of composite space. In fact, one problem is that constrained satisfaction problem is a apply heuristics for finding the non-straightforward path or complex environment [3, 4].

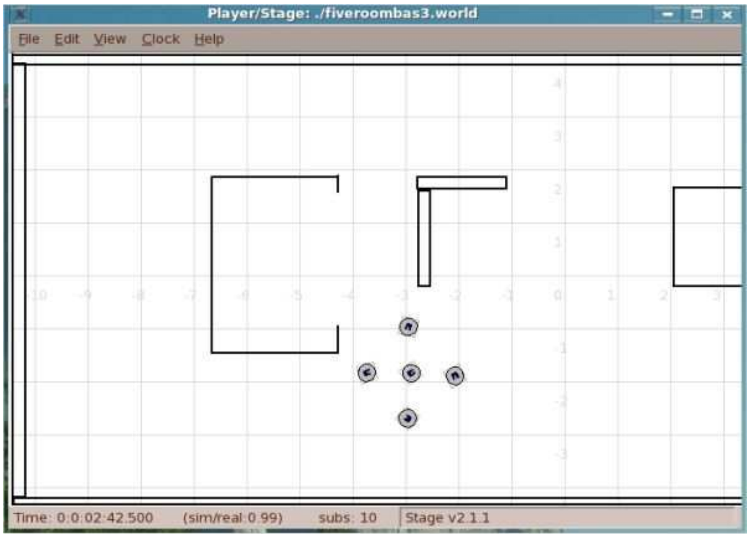

Figure 1. Path planning problem with three robots. The lines are the individual optimal paths for the robots between their current positions (indicated by large circles) and their goal locations (indicated by small dots).

A centralized path planning method which searches in the unconstrained composite configuration space is capable to determine the optimum solution to any finding issue when there is an answer. However, the time complexity becomes exponential for some of the robots [5]. Practical centralized approaches therefore either use heuristics to explore the huge joint state space, or constrain the configuration space to make the search feasible. As a result, they are typical neither complete nor optimal. Consequently, they may not succeed to find an answer even if it exists and the solution they generate may not be the optimal one.

As explained before decoupled planners first specify the track of the particular robot autonomously afterwards, utilize various strategies to eliminate probable conflicts. However, search space is still massive to treat with this issue; it is a proper decision to declare precedence to each robot [6]. The re-navigating step is then carried out in conformity with priorities. Thus, in the case of conflicts, prioritized approaches try to calculate a new trajectory which has no collision for all robots given the trajectories of the robots with higher precedence. Priority plans prepared an efficient technique for solving conflicts which is computationally effectual. Since they strongly restrict the search space, all decoupled techniques are also incomplete and generate potentially sub-optimal solutions that we derive approach from Maren thesis's [1].

The first examples illustrate the precedence plan that specifies the order where the paths of the robots are computed, has a significant effect on if an answer is findable and on the quality of the solution. Speaking roughly, this fact showed that no environment partitioning will be optimal that solved all robot movement issues in such complex environment.

In our research, a technique presented that looks up in the space of all precedence schemes when resolving complex multi-robot navigating issues. The proposed method employ a novel heuristic based partitioning method in the complex and 3D space of above definition. Because every replacement and modification of an algorithm needs to find the proper path for large number of robots, it is vital to concentrate on the search to achieve this, our approach applying restricts among the robots, based on the mission definition. There are two advantages. First on is minimizing the time needed to explore a solution (especially for real time calculation). Second is maximizing the number of problems while a solution is findable in a specific time interval. Moreover, our model is capable to decrease the total move cost upon a solution figured out. It has any-time attributes, in another word; the solution quality is planning on compute time.

The rest of our article is related work to multi-robot path planning emphasizing on prioritized decoupled methods. In Section 2 we present two prioritized decoupled path finding algorithms which are applied in the entire of this work and then describe our approach to searching for resolvable priority plans through navigating. Section 3 presents systematical experimental outcomes, representing the capacities of our algorithm to navigating and optimizing solvable precedence schemes.

2. RELATED WORKS

Many centralized algorithms apply possible field methods to direct the search [7-9]. These methods use various techniques to treat into the issue of finding the Ridge in optimization problem of finding path. Additional techniques limited such movements of object to minimize the bigness of that search tree for reducing the complexity of environment. For instance, Kuffner et al. [10] and Bhattacharya et al. [11] bound the paths of the robots to became a self-dependent map. These articles show the relation and harmonization which is result of exploring in a product named Cartesian of individual environment map. The particular roadmaps are constructed beforehand by randomly generating collision-free configurations and connecting them using some local planner. Bohlin et al. [12] presented a similar approach for robotic systems with many degrees of freedom. They directly build probabilistic roadmap (PRM) for the whole system. In this research once a roadmap has been learned it is usable to achieve conflict-free trajectories for different configurations of the robots as long as the environment does not change. Yousif et al. [13] proposed a variant which reduces the number of collision checks for the sampled configurations. Their goal has been to speed up the roadmap construction phase to efficiently answer single planning queries. The latter two roadmap methods, however, are not feasible for path planning problems with many robots. As we mentioned later, we solve the problem of large number of robots with combination our method to prioritized variant.

Contrary, Decoupled planners, initially compute trajectories for the particular robots self-dependent afterwards try to solve probable conflicts between these paths. In [14], one useful decoupled method is navigating in the setting time-space is proposed. This method expands time axis of the configuration space of the robot. Methods of this group allocate precedence to the each robot and estimate the pathways of all robots that basis of the arrangement signified by the mentioned precedence.

Thereby, they incorporate the trajectories of the robots with higher into the configuration time-space of the robot under consideration. The method presented by Tian et al. [15] applies a determined arrangement and utilizes potential field methods in the setting time-scope in combination with genetic algorithm to avoid collisions. The approaches proposed by Wang et al. [16] moreover applies a determined precedence plan and selects random deflect for the robots with less precedence. A further technique to decoupled navigating is the track coordination technique and introduced by O'Donnell et al. [17]. The basis of this approach is scheduling techniques for restricted resources [18]. The main thought of this study is to hold each robot on its own pathway and assume actions for the robots such as stopping, moving forward and moving backward on their tracks to prevent conflicts.

3. PROPOSED METHOD

Our model uses the A^* [24] or in Maren homepage ("*hrl.informatik.uni-freiburg.de/**maren**.html*") to measure the cost of optimum pathways for particular robots. The A^* directs issue of determining an optimal track according to a given cost function from a *start position* to a *target position* in an area which is a graph here. In order to perform exploration effectively, the A^* considers the gathered cost of achieving state *n* from the initial state start and similarly estimates the cost of achieving the goal state goal from *n*. The estimated cost is also called *heuristics*. A typical implementation of the A^* algorithm uses a priority queue which contains the already "*visited*" nodes along with their associated A^* costs. The A^* cost $f(n)$ of a node *n* are the accumulated costs *cost_from_start* [*n*] for reaching *n* from the initial state plus the estimated cost $h(n, goal)$ for reaching the goal state from *n*. In each iteration the element with the minimum A^* cost is extracted from the priority queue. If necessary its neighbors costs are updated by taking into account the cost between two neighbor states. These costs are given by the function *c*.

By using a good heuristics for the total cost of reaching the goal position, A^* attends to concentrate that the whole search space is more complex and to discovering a cost-optimal track. Mentioned feature leads A^* to be so effective search method and has given it great attention in the robotics. To ensure that the algorithm computes the optimal path the heuristics has to be admissible (prove at [25-33-35-34] and see [30-31]), which means that it does not overestimate the true cost to reach the goal.

It should be mentioned that A^* needs a discrete search graph, while the setting space of a robot is continuous. Furthermore, each state needs to have a finite number of successor states. Our assumption is that the area is described with a detached occupancy framework map. Occupancy grids divide the area into a framework of even distanced cells and keep in the cells $\langle x, y\rangle$ the possibility $P_{occ}(\langle x, y\rangle)$ which is contained a constant object. In other words, an occupancy grid map can be seen as a discrete graph: Each cell of the grid represents a node of the graph. For all neighbor cells with an occupancy value lower than a threshold, an edge between the nodes is inserted. The expense for traveling the cell <*x*, *y*> is related to its possession possibility which is denoted as $P_{occ}(\langle x, y\rangle)$. (occupancy) to prevent that pathways end to walls etc. We utilize a threshold function $\gamma(P_{occ}(\langle x, y\rangle))$ which $P_{occ}(\langle x, y\rangle)$. is endless if $P_{occ}(\langle x, y\rangle)$ overstep 0.8, and $P_{occ}(\langle x, y\rangle)$ otherwise. Moreover, the measured cost for getting the target state $\langle x^*, y^*\rangle$ is approximated by $\min_{occ} \cdot \left|\langle x, y\rangle - \langle x^*, y^*\rangle\right|$ while $\min_{occ} > 0$ is the optimal path. Otherwise, the expense for traveling the cell <*y*, *x*> is related to it's strongly possibility which is denoted as $C_{occ}(\langle x, y\rangle)$. (Carriage path) to prevent that robot to dealt with moving object. We utilize another threshold function $T(C_{occ}(\langle x, y\rangle))$ which calculate the Rigged value of each possible movement path. In figure 2, A* searched a space. In determined occasion the robot commence in the hallway of area to its aimed position located in south. Moreover, it presents the gathered costs of the states resulted by the finding procedure. A* not expands a large percents of the total state area and consequently is more effective.

A* drawback occurs in the situations that certainly no action is remaining. For some robot's that works on partially observable environment operations, at first we should apply the value iteration method for non-deterministic actions that is hardly better than A*. In other word, for changing the finding path to the best and most fit road we employ a SMA-iterative method that was introduced in 2000 [14]. One same influence is as in general viewed while respecting stochastic movements: It presents a fine for traveling tight to save the path of robot in remaining near to barriers. Consequently, according to the paths computed by A* robots usually select tracks which are far from barriers.

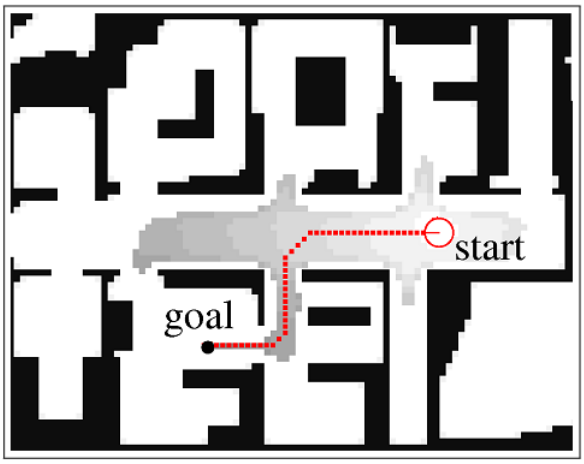

Figure 2. Result of a trajectory planning procedure for an individual robot applying A*. The gathered expenses Black Square respected while the search path are showed in grey (specially for starting and end point)

For basic comparison, an exemplary application instance of the prioritized decoupled finding methods is shown in Figure 4 (the image on left). In this position, the robot colored in green was assigned to reach the room 4located in north. The other robot (black robot) with its initial place in the hallway and its target place was near to initial position of the robot 1. When both pathways were designated self-dependent, a collision imposed among the two robots as shown in the figure. After utilizing A* in the setting time-space of the later (which we assumed to have lower priority), as illustrated in figure 4 (right side) the conflict is removed. Corresponding to the path computed by A*, the black robot must prevent the conflict with the green one by going to north where the other robot is supposed to enter the hallway (at the door). After this conflict avoidance process, the trajectory via the near doorway has lower cost. Figure 5 shows the trajectories of two robots carrying out the computed plans.

Moreover, in the best and generic implemented A* -based finding in the search space tree there exists a limited variant of this method that just investigates a subset of the outlinam to minimize the time of search. The trajectory coordination technique which proposed firstly by Donnell [17] restricts the search space to those situations which are on the individually navigated optimum tracks of the robots. Hence, robots have to remain in initially computed paths. In our work we use a prioritized variant of this approach. Regarding the constraints of the search space, the trajectory harmonization technique is more stable and was so popular than the tradition A*. Nevertheless, the main problem of this algorithm is related to this reality and hardly succeeds and that it often produces inefficient solutions.

Consider for example the occasion shown in Figure 4. In this occasion the path coordination technique cannot explore a trajectory for the green robot if the black robot has higher priority. Only if the green robot has higher priority the pathway finding issue is solvable by letting the black robot wait at its initial position until the green robot passed by. Figure 6 shows the related pathways achieved with the path harmonization method. Keep in mind that in this occasion the coordination method performs much worse than general A*-based navigating in the setting time-space. Since the coordination technique limits the nearest robots to remain on pre-calculated map, and then the robot starting in the start point and travel to the destination point on one crosses. Hence, the arrival time to reach its target point is nearly twice as long as not considering any collision. On the other hand, the two robots reach almost simultaneously applying unconstrained A*-based navigating in the setting time-space

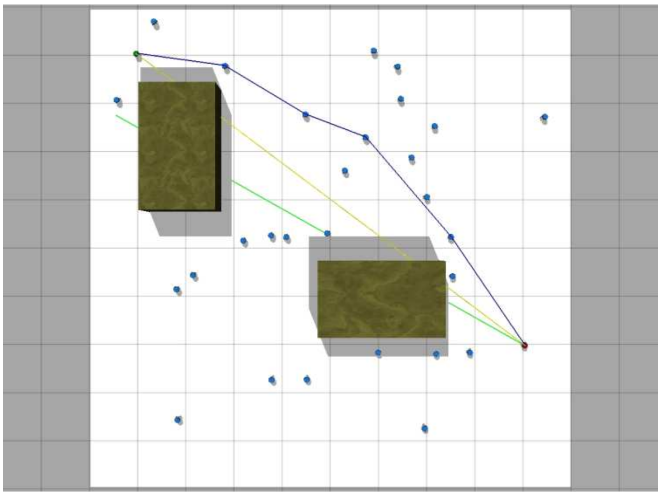

Figure 3. Average deflection of a robot from its pre-navigated track during plan execution. In a sequence of tests we constantly measured the distance of the robot's current location from own planned place at the same point in time. The distance unit is measured in *cm*.

Figure 4. Conflict occasion for two robots (image on left side) and resulting conflict-free paths after finding in the setting-time space of the black robot.

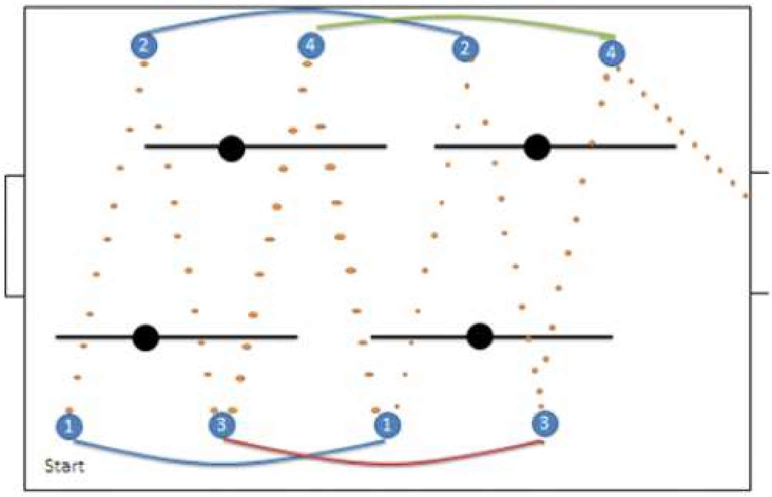

Figure 5. Resulting trajectories of two robots carrying out the planned paths illustrated in the Figure 4 (right side image).

4. EXPERIMENT & SOLVED PLANNING PROBLEMS

This first range of experiments was designed to define the effect of our search strategy on the overall number of planning problems that can be solved. We carried out 100 tests for each robot noticed . In each test we selected the beginning and goal positions of the robots by chance. Four different strategies were used , in order to discover a soluble precedence plans:

1. A selected arrangement for the robots which is chosen at random.
2. An arrangement which assures the limitations for the robots in R_1 and includes of a sequence for the robots in R_2 which is chosen randomly.
3. Unrestricted randomized inspection beginning with a sequence which is random and without attending the restrictions.
4. Restricted randomized inspections beginning with a sequence calculated similar to strategy (2).

Figure 6. The robots performing the navigation plans. The top left illustration plots the primary states. In the top right illustration robot 2 creates space for robot 1 while robot 3 takes a shortcut. The lower left illustration demonstrates robot 1 waiting to let robot 0 cross over. The lower right illustration plots robots last positions.

The second series of tests was carried out to check the capabilities of our method to guide the inspection in the space of all precedence plans. We were particularly interested in the question how much the calculation time essential to find a solution can be decreased by constraining the search. During these tests we increased the values of *maxFlips* and *maxTries* to 10 and measured in which iteration the first solution was found if the navigating problem could be solved. Figure 7 shows the outcomes achieved for different number of robots in the cyclic hallway field and Figure 5 plots the corresponding evaluation for the non-cyclic environment. We only evaluated planning problems which could be solved by both search methods.

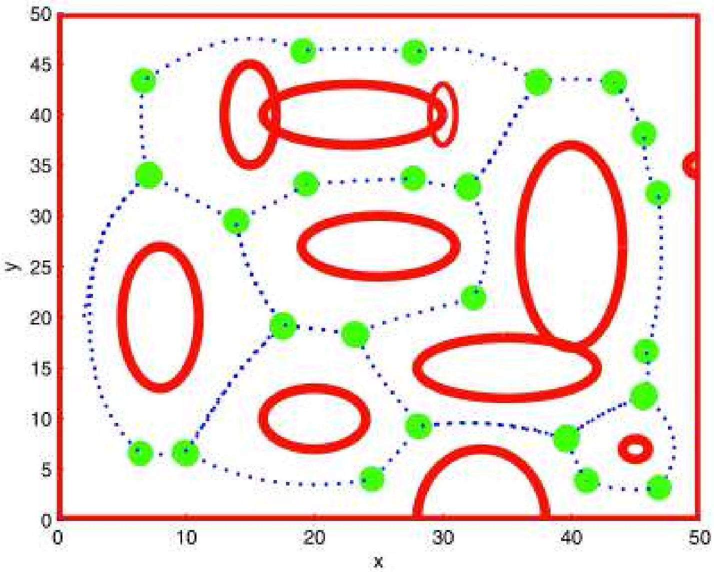

Figure 7. In the non-cyclic hallway environment we also have a significant difference between the two search strategies considering the iteration in which the first solution was found if the navigating problem could be solved.

The unconstrained search needs much more iterations than the constrained search to create a solution for both environments. Therefore, the benefits of our constrained search are two-fold. On one hand, it needs less iteration than the unconstrained counter-part. On the other hand, it needs less calculation, because the search is being limited to a subset of the robots, which decrease the number of trajectories that must be created in each iteration during the search.

Result in "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

5. CONCLUSION

In this paper we presented the main problems of the multi-robot path planning problem and explained the drawbacks of existing approaches. We introduced the prioritized decoupled path planning approach which searches in the configuration time-spaces of the robots for conflict-free paths. As pointed out, no single priority scheme for the robots would be sufficient to solve all possible multi-robot motion problems.

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