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Improved Backtracking Algorithm for Efficient Sensor-based Random Tree Exploration

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***Abstract*—Mobile robots need to explore novel environments to build useful maps for later navigation and motion planning. Sensor-based Random Tree, (SRT), technique had been used for exploration but it is problematic since the robot may visit the same place more than one time during backtracking process. In this paper, we propose a new heuristic algorithm to reduce this backtracking problem using the obtained map data. This algorithm is tested through computer simulations for several scenarios. The performance is evaluated in terms of exploration time, travelled distance and number of visited nodes. Since these classical evaluation metrics are correlated, we propose a new evaluation metric, that combines the total performance. The new algorithm is confirmed to reduce the exploration time of up to 30 %. The new evaluation metric is also shown to encapsulate the exploration performance and can be regarded as a much better representative of the performance that facilitate comparisons.**

I. Introduction

There is an increasing interest in autonomous mobile robot for applications in hazardous and inaccessible areas such as disaster sites, nuclear plants, volcanoes and space missions. Autonomous robots need an efficient strategy to explore novel environment where they have to work. Exploration enables the building of a map that will facilitate path planning and task execution in short time. Therefore, building efficient exploration techniques is both important and needed for autonomy. The exploration performance should be evaluated based on the objective of robot motion in the environment. However, the general objective can intuitively be stated as to gain maximum accurate information about the environment in the shortest possible time and minimum travelled distance.

Exploration is usually made in a greedy way, that is by approaching locations that maximize the acquired information, called frontiers. *Frontier-Based exploration* is common in almost all exploration techniques, and depending on the frontier selection mechanism, the literature can be broadly classified into the following three categories:

- Optimal-frontier.
- Behaviour based.
- Randomized motion.

In *optimal-frontier exploration*, the selection mechanism of the frontier can be varied according to a certain cost. For example, in [1] the minimum of the shortest paths to the frontiers over the global map was approached to minimize the total travelling cost. While in [2], both the expected benefit and the travelling path were considered when selecting among several frontiers in the global map. In *behaviour-based exploration*, the exploration process is decomposed into simultaneous simple reactive behaviours involving the repulsive and the attractive actions. For instance, in [3] a simple wall following behaviour achieved the exploration; while in [4], a combination of several weighted behaviours were fused together for efficient exploration. In *randomized motion planning* [5], robots were directed to acquire more information through random steps. Work in [6] is a typical example, where a randomized increments of a data structure called Sensor-based Random Tree (SRT) was generated. This tree represents the roadmap of the explored area with an associated safe region that depends on the sensor. Nodes of this tree are the visited explored locations. This basic SRT strategy was later modified by several researchers to enhance the process. For instance, in frontier-Based SRT (FB-SRT) [7], the random selection of target points was biased toward local frontier arcs in the current safe region. This improves the efficiency in terms of shorter travelled paths and more area coverage. In both strategies, SRT and FB-SRT, if there is no more unexplored area to approach, the robot goes back through previous nodes to find unexplored regions and explore again. This is called a *backtrack* strategy, which may cause long exploration distance and time, especially in environment with wide open spaces.

Several approaches were proposed to enhance the backtracking issue, in [8], bridges were added to the exploration tree to allow the robot to plan fast paths without looping all previous nodes. A bridge was added between two adjacent nodes having a common safe region between them and far away from each other by a certain distance larger than twice of the sensor range. That was done without taking into account the other valuable nodes that may exist between those two nodes. Special corridor environment simulated in

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[9] ensures that there is no need to travel all invaluable nodes between the final and the initial configuration, where planning a short path between them is possible and sufficient.

In this work, we are interested to build an efficient exploration algorithm that can satisfy time-critical applications such as rescue applications. For time critical application, savings in the exploration time is badly needed. Therefore, we observed that sensor based exploration is enjoying simplicity and completeness but may consume long time, mainly due to its backtracking technique. In this paper we will propose modification to the *backtracking* based on a simple heuristic algorithm. This new algorithm will approach the most informative node directly rather than travelling across all previous nodes in order.

The method proposed in this paper can be regarded as a combination of the optimal frontier and the randomized motion planning strategies. Random exploration planning is applied in the forward mode, while optimal node is approached in the backward mode with a heuristic planning algorithm. We devised a new exploration metric that encapsulates the relevant exploration variables, and is suitable for measuring the performance and for comparing exploration algorithms.

This paper is arranged as follows: In the next section, Sensor-based Random Tree, SRT, exploration strategy is briefly outlined. In section III, the new exploration technique is described. Simulations running on different exploration scenarios, are presented in section IV. The results are compared with the main sensor-based technique and presented also in section IV. Finally, conclusions are drawn in section V.

II. Sensor-Based Random Tree Exploration

The Sensor-based Random Tree, SRT [6], is based on a random selection of robot configurations inside the Local Safe Region, (LSR). LSR represents the free space around the robot at the current configuration q_{curr}; where its shape depends on the sensor characteristics as described in [10]. A road-map of the visited configurations, with the associated safe region, is represented by an incremental data structure called Sensor-based Random Tree (SRT). Each node in the tree represents the explored visited location.

Pseudo-code of the SRT strategy is shown in Algorithm 1. The algorithm starts at the current configuration q_{curr} acquiring the sensor measurements. The local safe region S and q_{curr} are added to the tree T. Then, a random angle θ_{rand} is generated to select the direction of travel along distance r in the LSR, which is calculated by the **RAY** function. According to this random direction, a random candidate configuration q_{cand} will be selected inside S.

The candidate configuration q_{cand} will be tested to validate two conditions; firstly, it must be at a distance farther than the current configuration at least by d_{min}. Secondly, it should not belong to any other LSR in the exploration tree T; as shown in Fig. 1. Note that, letting the constant $\alpha \leq 1$ will guarantee that q_{cand} is within the safe region and hence no collision avoidance is needed. If there is no configuration satisfying the requirements, backtrack, or *homing*, step will start,to travel along previous nodes to find unexplored region.

Algorithm 1: A pseudo-code for Basic SRT algorithm.

Build_SRT($q_{init}, K_{max}, I_{max}, \alpha, d_{min}$)

$q_{curr} = q_{init}$;
 for $k = 1 \rightarrow K_{max}$
 $S(q_{curr}) \leftarrow$ **PERCEPTION**(q_{curr});
 ADD($T, (q_{curr}, S(q_{curr}))$);
 $i \leftarrow 0$;
loop
 $\theta_{rand} \leftarrow$ **RANDOM_DIR**;
 $r \leftarrow$ **RAY**($S(q_{curr}), \theta_{rand}$);
 $q_{cand} \leftarrow$ **DISPLACE**($q_{curr}, \theta_{rand}, \alpha.r$);
 $i \leftarrow i + 1$;
until(**VALID**(q_{cand}, d_{min}, T) or $i = I_{max}$)
if VALID(q_{cand}, d_{min}, T)
 MOVE_TO(q_{cand});
 $q_{curr} \leftarrow q_{cand}$;
else
 MOVE_TO($q_{curr}.parent$);
 $q_{curr} \leftarrow q_{curr}.parent$;
return T;

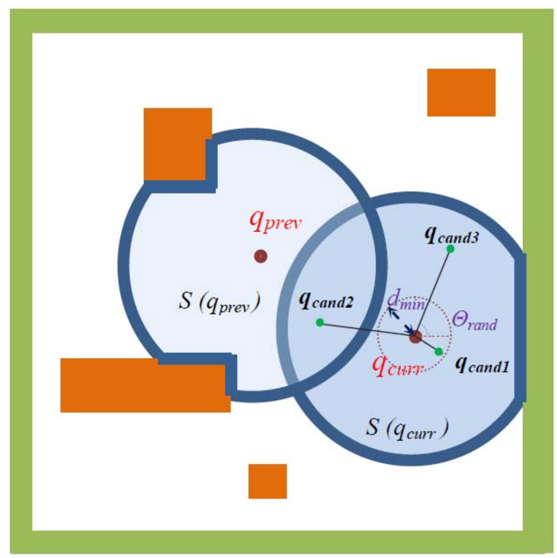


Figure 1: Validation of different candidate configurations in SRT: q_{cand3} is accepted, while q_{cand1} and q_{cand2} are not.

III. The New Approach

In SRT, and in case of no more valid configurations to reach, the robot traverses the q_{curr} parent node, searching for new candidate locations. This *backtrack* step wastes more time and is neither justified nor necessary.

In our approach, Algorithm. 2, the forward mode exploration is done as in the basic SRT method. In *backtrack*

Algorithm 2: A pseudo-code for Enhanced SRT algorithm.

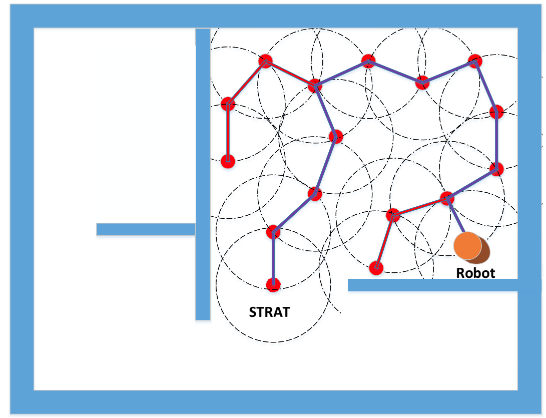
Enhanced_SRT$(q_{init}, K_{max}, I_{max}, \alpha, d_{min}, G_{thresh})$

$q_{curr} = q_{init}$;
for $k = 1 \rightarrow K_{max}$
$S(q_{curr}) \leftarrow$ **PERCEPTION**(q_{curr});
ADD$(T, (q_{curr}, S(q_{curr})))$;
$i \leftarrow 0$;
loop
$\theta_{rand} \leftarrow$ **RANDOM_DIR**;
$r \leftarrow$ **RAY**$(S(q_{curr}), \theta_{rand})$;
$q_{cand} \leftarrow$ **DISPLACE**$(q_{curr}, \theta_{rand}, \alpha.r)$;
$i \leftarrow i + 1$;
until(**VALID**(q_{cand}, d_{min}, T) or $i = I_{max}$)
if VALID(q_{cand}, d_{min}, T)
MOVE_TO(q_{cand});
$q_{curr} \leftarrow q_{cand}$;
else *% Modifications done to the backtrack*
% prepare the parent node to be tested
$q_{curr} \leftarrow q_{curr}.parent$;
loop
$q_{test} = q_{curr}$;
% calculate the information gain for q_{test}
$G =$ **GET_GAIN**(q_{test});
$q_{curr} \leftarrow q_{curr}.parent$;
% exit if the tested node is valuable
% or the configurations tree is empty.
until$(G \geq G_{thresh}$ or $q_{curr}.parent = NULL)$
% if the tested node is valid
if$(G \geq G_{thresh})$
% plan a shortest path to reach
APPROACH(q_{test}, T);
$q_{curr} \leftarrow q_{test}$;
else
% approach the initial node for homing
APPROACH(q_{init}, T);
$q_{curr} = q_{init}$;
return T;

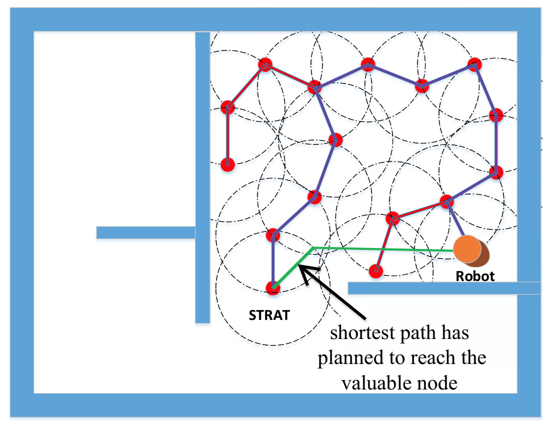
mode, after no more valid configurations to reach, it is proposed for the robot to review all the previous visited nodes in reverse order and selects the most informative node to approach. This informative node is estimated to have more information to acquire than other nodes in the tree. In other words, the robot is asked to travel over parent nodes by calculations rather than by itself, searching for valuable node to reach. A shortest path is then planned to this winning node, which is expected to enhance the exploration and reduce the total travelled path. The basic idea for enhancing backtracking in SRT is shown schematically in Fig. 2. In the basic SRT strategy, after no unexplored areas exist, the robot backtracks all the previous nodes till exit from the current explored room. While in our enhancement, the robot expects the starting node as a valuable node to reach. A shortest path, with the help of the built LSRs, is planned to approach this node of interest, saving distance and time.

The following explicit assumptions are needed for our exploration approach:

- The exploration environment is planar, i.e. $\mathbb{R}^2$, due to the nature of the planar range sensor used.
- Robot self-localization is done by another separate module.
- The robot is holonomic, i.e., it can turn in any direction without moving its pivot point.



a)



b)

Figure 2: A sketch showing a robot exploring a room using a) basic SRT strategy and b) the enhanced approach, where a shortest path, in green, is planned to the most informative node.

A. Map Building

Mapping is an essential process of the exploration task. A spatial representation for the unknown environment is required for both the consequent tasks, such as security or surveillance, and also for helping the robot to navigate the environment in the *backtrack* mode. In this paper, the occupancy grid based map is used for the representation. The environment is divided into small grids, each containing a value that represents the probability of being occupied by obstacles. It is necessary to know for each cell whether it is unknown, free, or an obstacle. Initially, the map is assumed to be unknown. Given a range scan and the robot pose, the occupancy grids within the sensor range are updated as follow; firstly, scan readings are converted to Cartesian coordinates of the occupancy grid map, creating a polygon of points. Secondly, this polygon is identified as the (LSR) and filled using flood-fill algorithm. Thirdly, obstacle cells are identified by the sensor readings that are smaller than the maximum sensor range R_{max}. The subsequent processes are shown in Fig. 3.

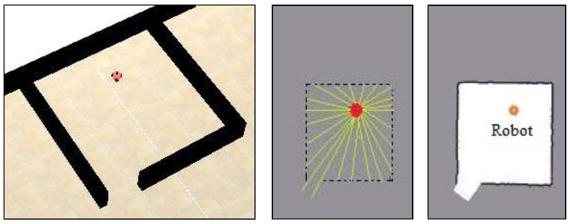


Figure 3: Building occupancy grid map using scanner range data.

B. Improved Backtrack Strategy

In the original SRT method, if there is no valid configuration to reach, the robot will backtrack over previously visited nodes, searching for new information to acquire. This step consumes more path length and more exploration time by visiting the same nodes without any additional information. In the new approach, after no valid configuration exists, robot selects the most informative node among those previously created nodes. This informative node is expected to have information gain more than a certain threshold G_{thresh}. This threshold is directly proportional to sensor maximum range.

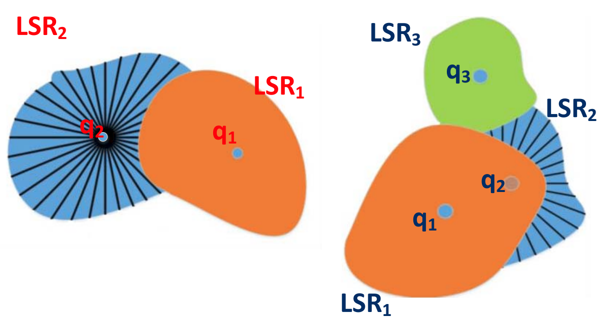


Figure 4: Estimation of information gain at different configurations by the use of ray-casting technique.

Estimation of the information gain that could be obtained at any point is a bit difficult. In fact, the actual gain is hard to predict as it varies according the structure of the corresponding region. In [11], this gain has been calculated by counting the number of unknown cells laying in a particular region surrounded by the maximum sensor range. This method did not guarantee correct estimation; as some unreachable unknown regions could be counted. In [12], the information gain was approximated as the relative difference between the current map entropy and the expected entropy after the simulated robot step at candidate location. This approach requires scanning all cells in the global map.

In our proposed algorithm, a simple heuristic *ray-casting* [13] method applied to estimate how much a certain node q_{test} will be valuable. During the ray-casting, the number of configurations traversed by the rays and that could contribute to the exploration process are recorded, and the sum of all the valid configurations traversed by the rays is used as a measure of how much information gain can theoretically be obtained from a particular node. This suits the laser scanner sensor used, where the number of scan rays and the angle between them depend on the characteristics of the actual sensor used. Valid configurations should meet the following conditions: (i) be at a distance larger than d_{min} from q_{test}, and (ii) not fall in the LSR of any other node belonging to the tree T . This is shown in Fig. 4, where the tested node q_2 on the left is estimated to have more information gain; $G \geq G_{thresh}$; than the node q_2 on the right.

After identifying the informative node, a shortest path is planned to reach it. This saves more exploration distance and time rather than visiting all previous nodes. The shortest path is planned using the A^* algorithm [14]. Dimensions of the robot are taken into account while planning the path by eroding the partial built map with a disk structure element. Unknown and obstacle cells are avoided during robot navigation.

IV. Simulation Results

Several simulation scenarios have been implemented to validate the new exploration approach. The 3D mobile robot simulator Webots [15], developed by cyberbotics, was used in all our simulations. A three-wheel omni-directional robot has been used in simulations. The robot has a diameter of 0.2 m and carries a 360^o laser range finder. In simulations, the parameters for the SRT algorithm were selected as follow: $\alpha = 0.9$, $d_{min} = 70cm$, $G_{thresh} = 100$ cells. The performance of the developed approach is compared with the basic SRT approach through several metrics:

- The travelled distance, TD, (total distance travelled by robot after returning back to home position).
- The exploration time, ET, (the time taken by robot to complete the exploration process).
- The number of nodes created in the tree, N_{nodes}.
- The completeness, C (the percentage of total area covered after the homing step):

$$C = \frac{Known\ Cells}{Map\ Width * Map\ Height} * 100\% \quad (1)$$

A flat environment was simulated to compare our developed approach with other strategies, as shown in Fig. 5. Roadmap produced of the developed approach and a comparison with

Table I: Simulation results of the exploration scenario

Strategy	ET(sec.)	$C\%$	TD(m)	N_{nodes}	EM
Perceptual Range R_{max}= 1 m					
Basic SRT	536	97.2	336.5	193	2.99
Enhanced SRT	360	97.1	217.7	182	7.29
% of Reduction	32.8	-0.1	35.3	5.7	
Perceptual Range R_{max}= 2 m					
Basic SRT	281.00	99.0	180.06	52	5.98
Enhanced SRT	237.00	98.5	146.95	50	14.58
% of Reduction	15.7	-0.5	18.4	3.8	

the original SRT approach are shown in Fig. 6. Nodes created and travelled paths are shown in green and blue, respectively, while the shortest paths planned by the enhanced approach are shown in red. In SRT strategy, red edges means that robot has backtrack them to return to it's home position. A comparison between the new approach and the basic SRT approach is given in Table I in terms of the mentioned metrics at different sensor range, 1 m and 2 m. Values are averaged over five simulation runs with different initial configuration.

The modification done to the backtrack step has proved a significant decrease in the total path length and the total exploration time in comparison with the basic SRT method, as summarized in Table 1. Also, the complexity of exploration process is reduced through the decreased number of tree nodes. Significant reduction in the exploration distance appears clearly in the scenario with smaller sensor range. This can be attributed to extreme number of exploration edges required to fill the entire open space.

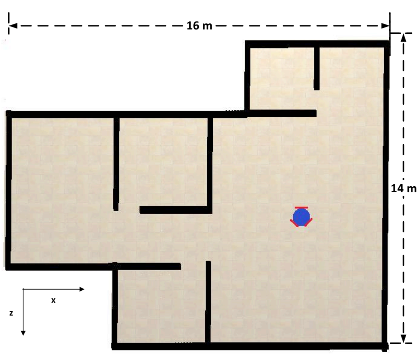
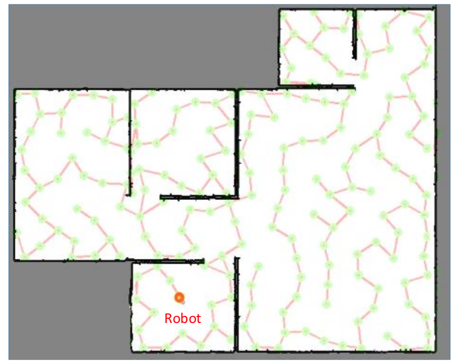
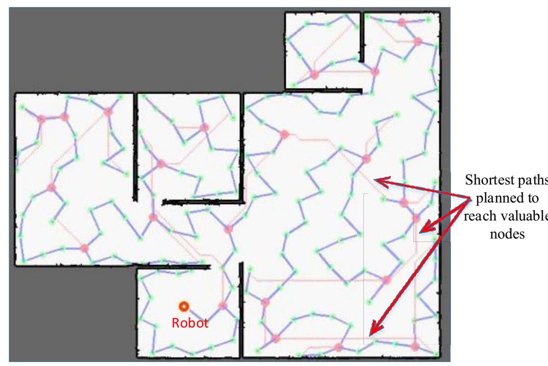


Figure 5: The environment used for the simulation scenario .

However, there is a trade-off among the metrics on which the performance of an exploration strategy can be evaluated; namely, exploration efforts (distance and time) and the percentage of area covered (completeness). The developed approach provides nearly complete coverage. Also, as shown in Table 1, the completeness percentages in the enhanced approach are comparable to those of the original SRT method, while exerting less effort. A single Exploration



a) A robot exploring a flat environment with basic SRT exploration strategy.



b) A robot exploring a flat environment with Enhanced-SRT exploration strategy [short-cuts between nodes are shown in red].

Figure 6: Simulation steps comparing a) the original SRT approach and b) the enhanced SRT exploration.

Metric', (EM), is proposed to judge over the performance of different exploration strategies. Intuitively, this index can be formulated based on its relationship with the mentioned metric. (EM) is proposed to be directly proportional to the completeness (C), and is inversely proportional to the normalized exploration time, ET_n, the normalized travelled distance TD_n, and the complexity F_n represented by the normalized number of nodes. The larger the values of this index, the better the performance of a strategy. The proposed index can be defined as follows:

$$EI = \frac{w_c * C}{w_t * ET_n \times w_d * TD_n \times w_f * Fn} \quad (2)$$

where w_c, w_t, w_d and w_f are the proportional weights added to measure the contribution of each factor to the metric. Normalization has been made with respect to an ideal exploration scenario that gives minimum exploration efforts. This situation is made by moving the robot in parallel horizontal paths separated by twice the sensor range $2R_{max}$ to cover the entire space, while assuming obstacle-free environment. This ideal scenario achieves minimum exploration distance of 100 m, travelling time of 105 $sec.$ and 102 nodes for the considered explored environment using the 1 m perceptual range. The number of nodes will decrease to 51 for the 2 m perceptual range. The proportional constants are taken equal to 1. As shown in Table. I, the new approach showed higher indices compared to the basic SRT at different perceptual ranges. This proves that the developed backtracking strategy improves the exploration process using this single exploration metric.

V. Conclusions

The Sensor-based Random Tree exploration algorithms had been modified in this paper to reduce the exploration time to suit time-critical applications. The key of the new approach is the selection of valuable regions to be explored, rather than backtracking all unnecessary explored areas. Shorter exploration paths improved the efficiency of new exploration technique. Several exploration scenarios had been simulated, with different perceptual range. The modified algorithm improved the exploration significantly, for example the exploration time was reduced by up to 30 %.

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