Partially Unknown Environment Exploration Algorithm for a Mobile Robot

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Abstract- This paper introduces a new indoor environment exploration method, which is designed to consider robot sensory perception constraints and indoor spaces predictable structure. Our new method is compared with a greedy approach exploration. The two algorithms were implemented and tested in simulation and in real-world experiments with a Russian Servosila Engineer crawler rescue robot. Robot Operating System (ROS) framework was used both for simulations in Gazebo environment and for the real robot control. Our method demonstrated better results for large space exploration in simulations as well as within small indoor environment exploration experiments.
Keywords: mobile robot, mapping, SLAM, navigation, exploration algorithm, Servosila Engineer.

1. Introduction

Active use of mobile robots in various fields around the world increases on a daily basis. Among a broad variety of robotics application domains mobile robots play important role in professional operations where it is necessary to extend capabilities and increase safety of a human, including urban search and rescue (USAR) [1], underwater [2], underground [3] and space exploration [4], as well as military application domains [5]. For rough terrain scenarios crawler robots are preferable due to their better mobility (relatively to wheeled robots) and higher load capacity (relatively to legged robots) [6]. Crawler robots are capable to overcome complicated obstacles, grass and rocky terrain, uneven surfaces and post-disaster urban indoor and outdoor debris environments, which make them most appropriate robots for USAR tasks [7, 29].

To build a fully autonomous mobile robot is a rather complicated task [8]. Thus, while due to the complexity of search and rescue tasks in real world environment a teleoperation control mode is still preferable to autonomous or semi-autonomous rescue robot systems [9, 10], researchers attempt automating particular functions of a robot in order to perform certain tasks [11, 28, 34].

A mobile robot is required to accomplish various tasks during its motion: it permanently performs simultaneous localization and mapping (SLAM) using on-board sensors, path planning and replanning while continuously collecting data about environment and surrounding objects, etc. To perform unknown or partially unknown environment exploration a robot updates an existing map and explores unknown regions of environment. The problem of environment exploration was previously tackled by a number of researchers while concentrating on a best exploring position search method for a single robot [12], multi-robot exploration using greedy algorithms [13] or complex indoor environment exploration strategies [14]. However, these methods were tested in environments that did not have real-world explorations features, e.g., map impulse noises, sensory data processing errors, robot perception limitations, etc.

Successful indoor environment exploration is especially crucial for urban search and rescue applications [15, 31]. This paper introduces our novel algorithm for indoor environment exploration. It considers robot sensory perception constraints and indoor spaces predictable structure. Our new method is compared with a standard greedy approach that uses optimization with regard to information gain regions [13, 30]. The two algorithms were implemented and tested in simulation and in real world environment experiments with Servosila Engineer robot [16, 32, 33]. Robot Operating System (ROS) framework was used both for simulations in Gazebo environment and for the real robot control. Our proposed algorithm uses local goals exploration approach on its way to a global goal. It was compared with a greedy approach that does not have a local goal selection feature and targets solely for a global goal.

Our method demonstrated better results for large space exploration in simulations as well as in the field experiments in several small real-world indoor environments.

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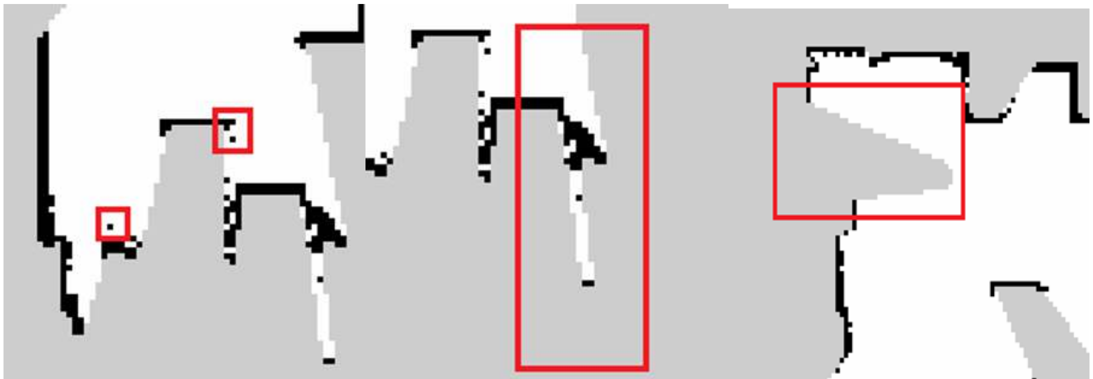

Figure 1. The maps are constructed by Servosila Engineer robot during an experiment. Mapping artifacts are encapsulated in the red rectangles: impulse noises (left), a processing error (center), a space between distinct laser scans (right).

2. Autonomous Exploration and Mapping

Laser range finder (LRF) is a popular tool for environment mapping that allows saving data in a form of an occupancy grid, where every cell value represents obstacle presence in a particular map region [17]. However, LRF sensors have several drawbacks, which should be taken into account during exploration: LRF devices have scanning angle limitations, obstacles constrain scanning regions and generated maps may contain noise or incomplete data. Moreover, since most mapping algorithms rely on odometry data [18], usually a map contains data processing errors and various artifacts (Figure 1) that significantly influence SLAM performance of a mobile robot [19]. A number of such errors and artifacts could be reduced if a mapping algorithm takes into an account some particular environment features. In our case, we could utilize indoor environment predictable features of structured rooms and corridors that are surrounded by walls.

Exploration Approach

The proposed approach uses our previously developed map preparation tool that reduces noises on an existing map [20]. After noise reduction, a robot localizes itself on the incomplete map. While it is possible to do with Adaptive Monte Carlo Localization [21] that provides an acceptable localization accuracy even with unreliable mapping data, we used a predefined robot position in our simulations and experiments in order to eliminate influence of stochastic localization methods on exploration algorithms during the robot motion and to allow an objective comparison of the pure algorithms. The proposed algorithm uses local goals and is presented in Algorithm 1; it is further described in more details in this chapter. Algorithm 2 presents a greedy exploration approach that has no local goals feature, but similarly to Algorithm 1 takes into an account LRF's angle of sight and uses a configuration space, referred further as C-space [22], generation for safe motion. The two algorithms were implemented and compared in Gazebo simulation and real world experiments to estimate the benefits of using local goals by the new algorithm.

Algorithm 1 Proposed exploration algorithm

procedure Proposed_environment_exploration (*partially_known_environment_map*)
  Mark reachable information gain regions
  Create C-space for robot
  while Reachable information gain regions are available **do**
    repeat
      Select *global_goal*
    until path to *global_goal* does exists
    Select local goals on the way to global goal
    while local goals are available **do**
      while local goal is not reached **or** local goal is considered reachable **or** *target_region* exploration is not completed **do**
        Move to local goal
      end while
    end while
  end while
end procedure

Algorithm 2 Greedy exploration algorithm
procedure Greedy_environment_exploration (*partially_known_environment_map*)
  Mark reachable information gain regions
  Create C-space for robot
  while Reachable information gain regions are available **do**
    repeat
      Select *goal*
    until path to *goal* does exists
    Move to goal
  end while
end procedure

Reachable Information Gain Regions

In greedy approach, all unknown cells are included into information gain regions [13]. However, indoor environments have a predictable structure with walls and obstacles, and these features should be used for a more accurate reachable information gain regions marking.

In our approach, information gain regions are constructed recursively with Algorithm 3, which resembles a brushfire algorithm of Voronoi graph construction [23].

Algorithm 3 Proposed reachable information gain regions marking algorithm
procedure Proposed_reachable_marking (*partially_known_map, desired_depth*)
  Mark all unknown cells that are adjacent to obstacle-free known
  while *depth* < *desired_depth* **do**
    Mark all unknown cells adjacent to all cells marked on previous step
    $depth \longleftarrow depth + 1$
  end while
end procedure

The algorithm starts with adding unknown cells of a map, which are adjacent to obstacle-free cells (of the known part of the map), to the information gain regions. Next, adjacent cells to the ones already in the information gain regions are added to information gain regions, and the algorithm continues recursively.

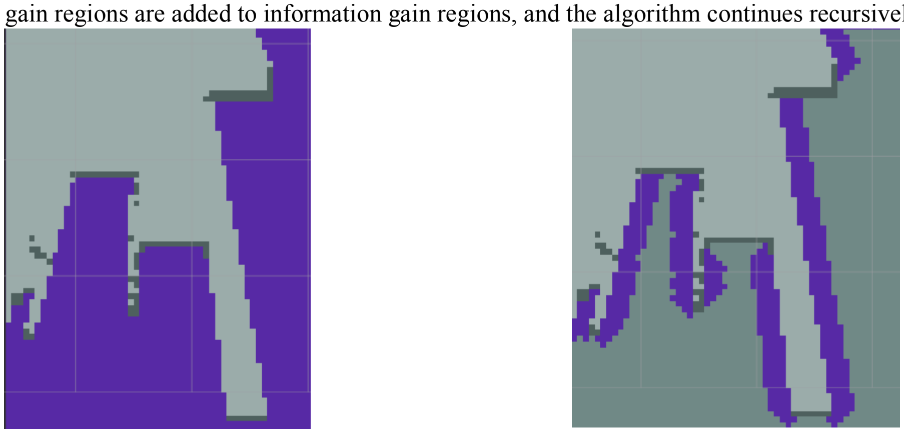

Figure 2. Greedy approach reachable information gain regions (left, highlighted in violet color) and our approach reachable information gain regions (right, highlighted in violet color). Free space within a map is colored in a light gray, walls are colored in dark gray and other unknown cells are colored in gray (in the right figure only).

The depth of recursion *desired_depth* is defined depending on map resolution and is set equal an environment wall thickness value, but should not exceed a range of robot sensor(s). This value was established empirically after multiple options testing within Gazebo simulation, and the idea behind such selection is an indoor environment structured pattern itself: as a robot moves farther away from a known space frontiers into an unknown region, the probability of discovering an obstacle that would limit further information gain (e.g., a wall) increases. The adjacency to obstacle-free cells requirement allows avoiding marking cells behind indoor structures (which generally could not be observed) at a low computational cost. Figure 2 depicts in a violet color information gain regions of a greedy approach (left figure) and our approach (right figure) for the same indoor environment.

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Algorithm 4 Proposed global goal selection algorithm
procedure Select_global_goal (*partially_known_map, desired_depth*)
  global_goal ← empty
  max_gain ← 0
  for all each cell K in C-space **do**
    gain ← G(K) // Reachable information gain cells count within the range of robot sensor
    if *gain* > *max_gain* **then**
      global_goal ← K
      max_gain ← G(K)
    end if
  end for
  return *global_goal*
end procedure

Algorithm 5 Greedy goal selection algorithm
procedure Select_greedy_goal (*partially_known_map*)
  global_goal_cand ← empty // Variable to store potential global goals
  unreachable_goals ← empty // List to store potential global goals considered unreachable
  global_goal ← empty
  while *global_goal* is empty **do**
    max_gain ← 0
    for each frontier cell K which is not in *unreachable_goals* **do**
      gain ← G(K) // Reachable information gain cells count within the range of robot sensor
      if *gain* > *max_gain* **then**
        global_goal_cand ← K
        max_gain ← G(K)
      end if
    end for
    if *global_goal_cand* is in C-space **then**
      global_goal ← *global_goal_cand*
      return *global_goal*
    else
      for each cell *L* in C-space in *sensor_radius* range from *global_goal_cand* **do**
        if *global_goal_cand* is on the line of sight from *L* **then** // Bresanham line algorithm is used
          global_goal ← *L*
          return *global_goal*
        end if
      end for
    end if
    unreachable_goals ← *global_goal_cand*
  end while
end procedure

Global and Local Goals Selection

The proposed Algorithm 4 sets a global goal in an obstacle-free cell, which has a maximum count of reachable information gain cells within a radius equal to the robot sensor range. The idea behind this is that when the robot reaches the global goal it will discover a maximum possible amount of new data with regard to our assumptions about environment structure. An additional condition of path existence toward the global goal is verified in order to avoid targeting unreachable cells. The information gain regions are constructed with a brushfire-type algorithm that prevents inclusion of cells, which are located behind blind walls. Therefore, unobservable cells do not affect the global goal selection process. The proposed algorithm has low computational cost and allows fast estimation of potential information gain.

Greedy approach global goal selection Algorithm 5 uses a different definition. While the original definition [13] considers a global goal as a frontier cell (between known and unknown parts of the map) with a maximum count of reachable information gain cells within the robot sensor range, there may be obstacles in unknown region near to this goal, which do not allow the robot to reach the goal due to physical sizes of the robot. To avoid this, after a candidate frontier cell GG_{cand} with a maximum count of reachable information gain cells within the robot sensor range is selected, the algorithm searches for cell GG_{free} of C-space closest to GG_{cand}. If there are no

obstacles in the line of sight between GG_{cand} and GG_{free} and a path from the robot current location to GG_{free} cell exists, this GG_{free} cell is accepted as a global goal.
The two approaches difference is demonstrated in Figure 3: while the greedy approach forces the robot to move directly to the frontier (even though there exist more optimal positions for observation), the proposed approach selects a position in a such way, that several unknown regions could be simultaneously observed.

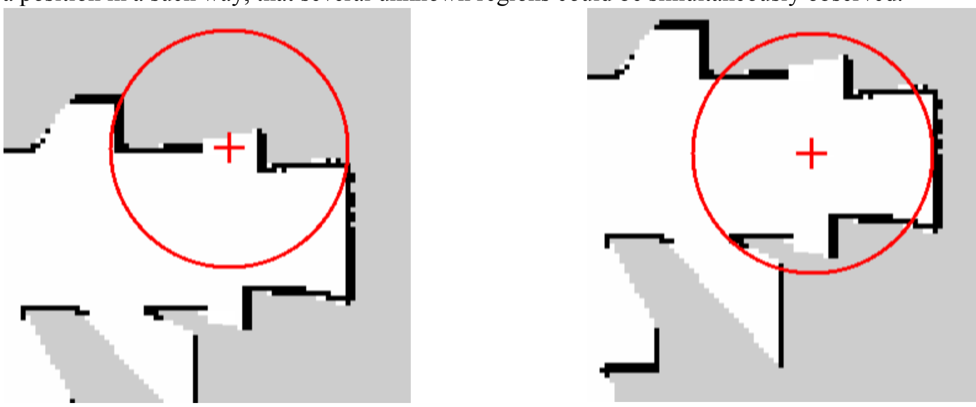

Figure 3. The red cross marks an observing point (a robot position) and the red circle represents a robot sensor range. Greedy approach observing point is located at the free space frontier (left) and our approach observing point is located in the free space with several unknown regions within sensory range (right).

Local goals are a special feature of our proposed approach. The idea behind is that local goals help to explore unknown regions more effectively while the robot moves toward the global goal. A proper selection of local goals prevents the robot from going back and forth multiple times when the global goal is reached and a new global goal is selected.
Local goals selection algorithm is described in Algorithm 6. First, a path to the global goal is calculated and discretized. Next, for every cell of this path a check for a reachable information gain region availability is performed within *search_radius* range from the cell. Examinations start from the current position robot location and goes sequentially through all path cells. If a reachable information gain region is detected, Bresenham line algorithm is used to test if this unknown region is observable from any position on the path, and a closest to the unknown region C-space cell is selected as a local goal.

Algorithm 6 Proposed local goal selection algorithm
procedure Select_local_goal (*partially_known_map, search_radius*)
  for each position P on the path to global goal **do**
    for each unknown cell U in *search_radius* from the P **do**
      if U is on the line of sight from P **then** // Bresanham line algorithm is used
        // Search for reachable cell which is the closest to U
        for each cell L on the line of sight **do**
          if L is in C-space **and** path there is path to L **then**
            local_goal ← L
            return *local_goal*
          end if
        end for
      end if
    end for
  end for
  return *no_local_goals*
end procedure

Figure 4 demonstrates an example of the greedy approach and our approach exploration performance. Red cross marks robot's initial position and red rectangles depict the unknown regions that should be explored by the robot and the numbers show the exploration sequence. With the greedy approach, the robot has to repeat a part of its path while moving from region 1 to region 2, and then to pass again through region 1 in order to reach region 3 because a global goal is set in region 1, 2 and 3 sequentially. With our approach, a global goal is set in region 3 and the robot sets automatically local goals in regions 1 and 2 and explore them on its way to region 3.

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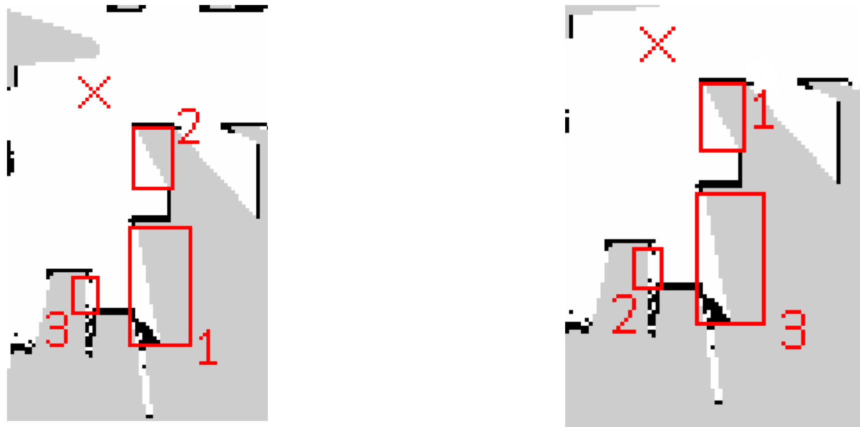

Figure 4. Greedy approach unknown regions exploration sequence (left) and our approach unknown regions exploration sequence (right). Red cross marks robot's initial position.

3. Simulation in Gazebo Environment

Automatic heightmap creation tool was used to create simulation landscapes from arbitrary graphical images [24]. An input image is filtered, cropped and smoothed out to be ready for import into Gazebo simulator in a form of .world file that stores entire data about a simulation. This file contains a landscape based on an input image, and Figure 5 demonstrates an example, which was used in our simulations.

The tool automatically performs image format conversion and size editing that are required by Gazebo simulator. In addition, it optionally allows performing noise filtering, image smoothing and color inversion if needed. A resulting 3D landscape is fully functional: it provides collision detection, texture mapping, light and shades processing.

For the simulations, it was substituted with TurtleBot robot model [25], which is a differential drive wheeled robot. *Kinect* device was used to perform scans with a narrow scanning angle of 60 degrees and *Gmapping* [26] package was used for scanning data processing.

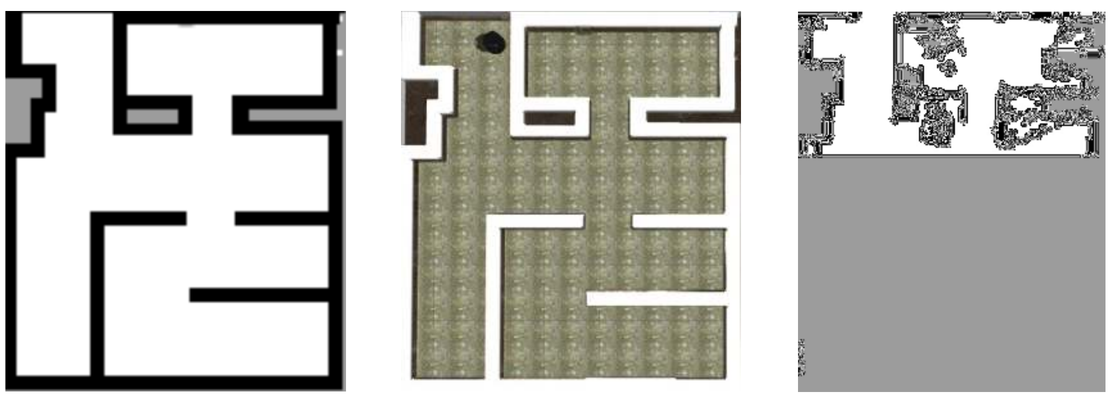

Figure 5. Automatic heightmap creation tool demonstration. Original map (left), and a 3D Gazebo simulation environment that was created using the original map (center). The map was used in simulations as an input for a robot (right).

An indoor environment with multiple dead ends was used for the simulation (Figure 5). The robot always started at the same starting point, and the simulation ended when the robot had completed the map exploration so that no unknown observable points were left within the map. Both algorithms, the greedy approach algorithm and our proposed method, were executed 20 times and total traveled by the robot distance was measured.

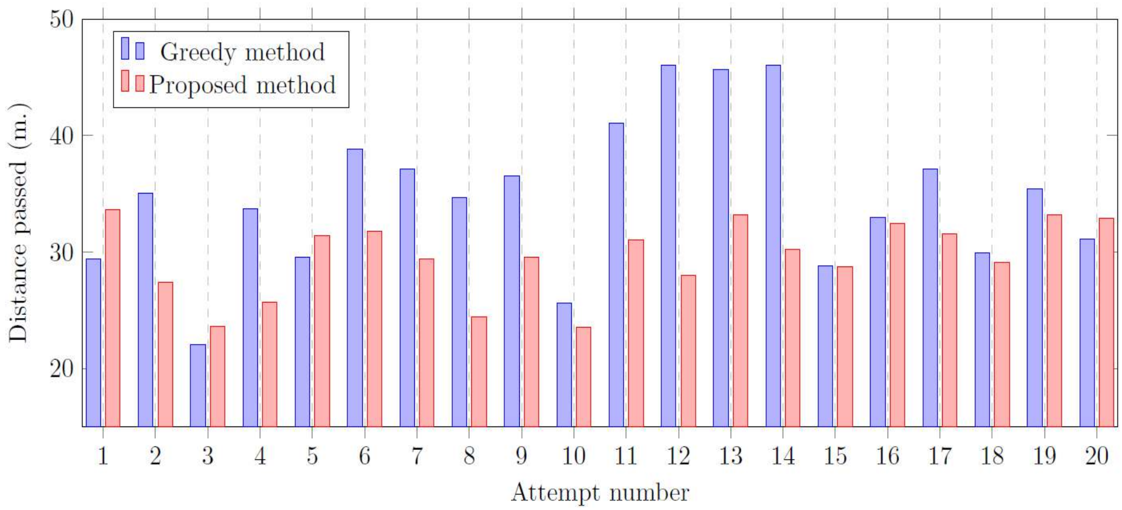

Figure 6. Distance traveled by the robot in Gazebo simulation for the environment in Figure 5.

Figure 6 demonstrates the results of 20 simulations for the two algorithms. The proposed method show better results in average – 34.84 meters were traveled using greedy approach, while only 29.57 meters were traveled using the proposed approach. Moreover, the proposed approach performs in a more stable way, reducing traveled distance standard deviation from 6.57 meters for a greedy approach to 3.22 meters for our approach. This feature allows predicting full distance traveled more precisely, which is important for robots with significant power constraints. Nondeterministic simulations performance with identical starting conditions were caused by a combination of its' external components drawbacks - the narrow scanning angle of *Kinect* device model and *Gmapping* algorithm implementation, which saves mapping data only when an object is detected by a scan and thus introduces a low map update rate in obstacle-free spaces. The simulations proved that the proposed method generates more stable and effective paths for partially unknown environment exploration, therefore experiments with the real robot using a LRF were conducted in order to verify the relative performance of the algorithms.

Figure 7. Servosila Engineer robot at starting position with LRF (encapsulated in the blue rectangle) installed on a stand with a voltage regulator and a voltage indicator (encapsulated in the red rectangle). The laser beam is parallel to the floor surface.

4. Verification Experiments

Experiments were conducted in a classroom 1403 of size 6 x 5.5 meters, which is located at Laboratory of Intelligent Robotic Systems, Higher Institute for Information Technology and Information Systems, Kazan Federal University, 35 Kremlevskaya str. The room was filled with obstacles of complex shapes, including tables, chairs and other furniture. The furniture was arrangement in two ways: the ordinary classroom arrangement kept an everyday natural furniture positioning (Figure 8) and for the classroom arrangement with several dead ends, which was manually created in order to verify algorithms behavior in a different environment, the furniture was distributed to form elongated obstacles and dead ends (Figure 9). The Servosila Engineer [27] robot starting position and orientation was kept the same for all trials (Figure 7).

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Table 1 demonstrates numerical results of experiments in the two classroom arrangements for the greedy algorithm exploration approach and our algorithm.
Each method was tested 10 times in each of the two obstacle configurations and total traveled distance was recorded. The attempts were independent and the resulting path of the two algorithms within the same line should not be directly compared. Moreover, since all attempts within the same room arrangements had identical starting conditions, all attempts for each room arrangement should be compared as two sets.

Figure 8. Ordinary obstacles arrangement in classroom 1403, 35 Kremlevskaya str.

Figure 9. Obstacles arrangement with several dead ends in classroom 1403, 35 Kremlevskaya str.

The experimental results confirmed that the proposed approach performs significantly better than the greedy algorithm approach for partially unknown indoor environment exploration. Figure 10 presents these results in a graphical form.

	Distance traveled before completing the exploration (m.)			
Environment	Ordinary classroom arrangement		Classroom with several dead ends	
Attempt	Greedy method	Proposed method	Greedy method	Proposed method
1	25,03	19,11	29,53	17,32
2	28,64	20,34	25,88	15,04
3	22,95	16,43	27,8	16,86
4	24,87	21,75	24,64	15,65
5	30,05	19,68	25,71	17,43
6	30,12	15,87	26,45	15,36
7	23,95	20,25	22,02	20,16
8	24,78	20,91	24,13	17,55
9	26,62	20,23	27,03	18,03
10	25,22	19,23	27,15	16,78

Table 1. Experimental results in different classroom environment arrangements

The average traveled distance of the proposed approach was 26% less in the ordinary classroom arrangement and 35% less in the environment with several dead ends.
In the ordinary classroom arrangement, the worst performance of the greedy algorithm was a 30.12 meters travel path and its best performance was a 22.95 meters travel path. At the same time, the worst performance of our new algorithm was a 21.75 meters travel path and its best performance was a 15.87 meters travel path. Thus, our algorithm worst exploration attempt path was still 1.2 meters shorter than the best attempt of the greedy approach. On the opposite, if we compare the worst attempt of the greedy approach with the best attempt of our algorithm, the later outperformed its counterpart almost in 2 times.

In the classroom arrangement with dead ends, the worst performance of the greedy algorithm was a 29.53 meters travel path and its best performance was a 22.02 meters travel path. At the same time, the worst performance of our new algorithm was a 20.16 meters travel path and its best performance was a 15.04 meters travel path. Thus, in these settings our algorithm worst exploration attempt path was still 1.86 meters shorter than the best attempt of the greedy approach. If comparing the worst attempt of the greedy approach with the best attempt of our algorithm, the later again outperformed its counterpart almost in 2 times.

The obtained via two sets of experiments results demonstrated that the proposed exploration tactics with all unknown regions on the robot path being explored while moving toward the global goal is significantly more efficient that a sequential global goal selection of the greedy approach since it allows the robot to avoid returning multiple times during exploration.

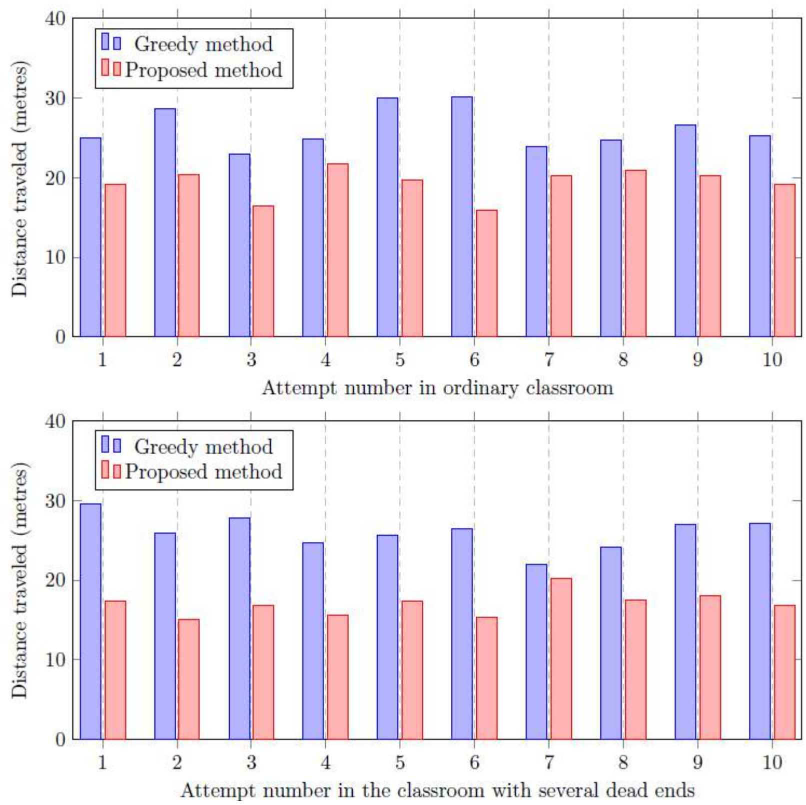

Figure 10. Distance travelled in the experiments: the ordinary classroom arrangement (top) and the classroom arrangement with several dead ends (bottom).

5. Conclusions

The long-term goal of our research project is to make possible efficient robotic systems usage in unreliable environment under conditions of incomplete or imprecise data about the environment. In this paper, we concentrated on a problem of partially unknown environment exploration with a single ground mobile robot. We proposed a new partially unknown environment exploration method, which considers input map uncertainty, sensory perception constraints, and restricted motion capabilities of a real robot and special features of indoor environment.

The proposed algorithm performs an efficient exploration due to defining a set of local goals that are explored on a robot way toward a global goal and save time for multiple returns of the robot to already-explored regions. We proposed a new definition of information gain regions, which takes into an account robot physical size and known obstacles of the environment.

The proposed method was compared with a greedy approach that uses a transferred into configuration space yet classical information gain region definition. The two algorithms were implemented in Gazebo simulator and next verified in real world experiments. The experiments with a LRF-equipped Servosila Engineer robot were performed within two different indoor environments. The proposed method demonstrated higher efficiency both in simulations and in verification experiments. Moreover, the worst real-world experimental trials of the proposed approach slightly outperformed the best experimental trials of the greedy approach in both environments.

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