Amsterdam Oxford Joint Rescue Forces: Team description paper: Virtual Robot competition: Rescue Simulation League: RoboCup 2009

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Arnoud Visser[1], Gideon Emile Maillette de Buy Wenniger[1], Hanne Nijhuis[1], Fares Alnajar[1], Bram Huijten[1], Maarten van der Velden[1], Wouter Josemans[1], Bas Terwijn[1], Christiaan Walraven[1], Quang Nguyen[1], Radoslaw Sobolewski[2], Helen Flynn[2], Magda Jankowska[2], and Julian de Hoog[2]

[1] Universiteit van Amsterdam, Science Park 107, 1098 XG Amsterdam, NL
[2] Oxford University Computing Laboratory, Parks Road, Oxford OX1 3QD, UK
http://www.jointrescueforces.eu

Abstract. With the progress made in active exploration, the robots of the Joint Rescue Forces are capable of making deliberative decisions about the distributing exploration locations over the team. To navigate autonomously towards those locations, the robots gradually aggregate their experience in a traversability map. This traversability map can be used as basis to calculate an optimal path towards a goal. Robots equipped with both camera and laser-range scanners can learn a visual classifier of free space, which could be used by robots without laser-range scanners to navigate through the environment. Part of our algorithms have been validated on the Nomad Super Scout II robot available in our laboratory.

Introduction

The RoboCup Rescue competitions provide benchmarks for evaluating robot platforms' usability in disaster mitigation. Research groups should demonstrate their ability to deploy a team of robots that explore a devastated area and locate victims. The Virtual Robots competition, part of the Rescue Simulation League, is a platform to experiment with multi-robot algorithms for robot systems with advanced sensory and mobility capabilities. The developed algorithms should be directly portable to fieldable systems, as demonstrated by several of the participating teams [1].

The shared interest in the application of machine learning techniques to multi-robot settings [2] has led to a joint effort between the laboratories of Oxford and Amsterdam.

1 Team Members

UsarCommander was originally developed by Bayu Slamet and all other contributions have been built into his framework. Many other team members [3–6] have contributed on perception and control algorithms inside this framework.

The following contributions have been made this year:

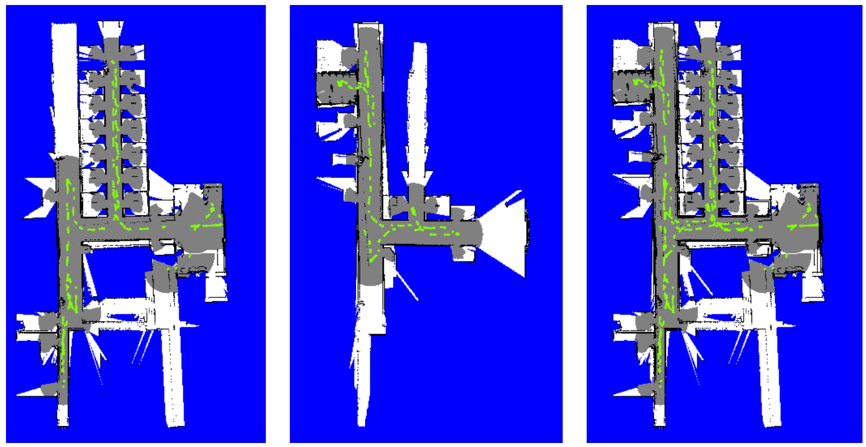
Arnoud Visser	: research portfolio [2], exploration algorithms [7], communication protocol [8], geometry, mapping test
Gideon Maillette de Buy Wenniger	: image interpretation, learning to visually recognize free space [9]
Hanne Nijhuis, Fares Alnajar	: teleoperation test, waypoint navigation with AirRobot [10]
Bram Huijten, Maarten van der Velden, Wouter Josemans	: generation and usage of traversability maps, A* path-planning
Bas Terwijn	: interface to the Nomad Super Scout II robot, software performance analysis
Quang Nguyen	: visual range scanner.
Christiaan Walraven	: map evaluation.
Radoslaw Sobolewski	: mobility challenges with Kenaf robot.
Helen Flynn	: automated map attribution
Magda Jankowska	: map stitching
Julian de Hoog	: user interface, hybrid autonomy, multi-robot exploration, communication roles [11], deployment test

2 Scan Matching

The possibilities for active exploration are heavily dependent on a correct estimation of a map of the environment. Many advanced techniques that aim to detect and correct error accumulation have been put forward by SLAM researchers. Although these SLAM techniques have proven very effective in achieving their objective, they are usually only effective once errors have already accumulated. With a robust scan matching algorithm the localization error is minimal, and the effort to detect and correct errors can be reduced to a minimum. Several scan matching algorithms are available in our code, but during the 2009 competition the WSM algorithm [12] will be used, based on the robustness reported in [13].

3 Localization and Mapping

The mapping algorithm of the Joint Rescue Forces is based on the manifold approach [14]. Globally, the manifold relies on a graph structure that grows with the amount of explored area. Nodes are added to the graph to represent local properties of newly explored areas. Links represent navigable paths from one node to the next.



(a) Map generated by one robot (b) Map generated by another robot (c) combined Map

Fig. 1. Map resulting from an autonomous exploration of the 2006 Competition world

The graph structure means that it is possible to maintain multiple disconnected maps. In the context of SLAM for multiple robots, this makes it possible to communicate the graphs and to have one disconnected map for each robot. The result is illustrated in Fig. 1, where the maps of two robots are merged into a single map for the operator. Also note the nice distribution of the exploration effort (fully autonomous) between the two robots. The graph structure of the manifold can be easily converted into occupancy grids with standard rendering techniques, as demonstrated in [13].

4 Traversability Map

An important aspect for a mobile robot is to have a good estimate of the quality of the terrain, before navigation decisions are made. An occupancy grid (the probability that an obstacle is present) is a good initial estimate, but this estimate is based on a 2D-range scan on a fixed height. The quality of the terrain can be misjudged, for instance by obstacles present on a different height. More fundamentally, there can be obstacles present which are extremely difficult to perceive (e.g. quicksand, tripwires), even when the output of many advanced sensors is combined. At the end, the ultimate way to learn the terrain quality is to try it out. In essence, the mobility experience of the robot is collected as a function of its position. The mobility success T can be measured with different metrics. During an exploration run several mobility features are stored in the nodes of the map. Currently, these features are the requested v_r and measured speed v_m. Additional features could be added, such as the tilting angle experienced by the Inertial Navigation System (INS). Those features are mapped onto a range between 0 to 255 by a utility function. The currently applied utility function is a linear relationship, as defined in Eq. 1:

$$T = 255\frac{|v_m|}{|v_r|},\ with\ T = 0\ when\ |v_r| = 0\ and\ T = 255\ when\ \frac{|v_m|}{|v_r|} \geq 1 \qquad (1)$$

The result is a traversability map which in the beginning mainly reflects the traveled paths (see Fig. 2), but when the experience of multiple robots from multiple runs is aggregated, the traversability map should gradually cover the map of free space.

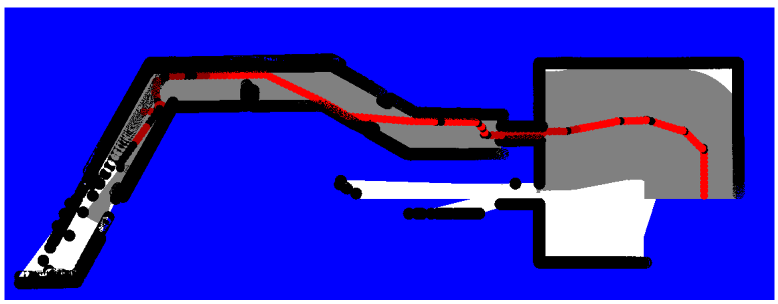


Fig. 2. Traversability map generated from a first exploration of the Mobility world

An advantage of this experience based approach is that it does not require very complex terrain models. In fact, the robot does not need to know anything about the terrain at all other than how fast it is moving over it. This means that this approach should work for any kind of terrain, be it in water, air, the desert or the red sands of Mars.

5 Path Planning

A robot can use a map, such as an a priori map, an occupancy grid map or a traversability map, to plan a safe path from a start position to a goal. Currently, two path-planning algorithms are available in our environment; a breadth-first algorithm [15] and an A* algorithm [16]. In both algorithms different types of maps can be included in the calculation of the distance measure $g()$, which calculates the 'real' costs to travel to an intermediate point on the path. The heuristic function $h()$ will estimate the distance to the goal, which can be a simple Euclidian distance (without notion of obstacles or traversability). Both algorithms are based on graph-search, but the difference between both algorithms is the way in which the graph is expanded. For the breadth-first algorithm all neighbouring grid cells (not considered before) are expanded, which is equivalent with using a first-in-first-out (FIFO) queue. For the A* algorithm all neighbouring grid cells are added to a priority queue, and the search continues with the most promising node (which doesn't have to be neighbour). The sorting of the priority queue[3] is based on the distance measure $f() = g() + h()$. This algorithm is illustrated in Alg. 1.

```
Data: the traversability map m, the start point s, the target point t
Result: the optimal path p from location s to the location t
closed = EmptyList();
open = EmptyPriorityQueue(s);
while Not IsEmpty(open) do
    c = HighestPriority(open);
    if h(c,t) < ϵ then
        Return p(c);
    end
    if Not IsMember(closed,c) then
        closed.Add(c);
        for each neighbor(c,n) do
            d_n = g(s,c,m) + h(n,t);
            p(n) = p(c) + n;
            QueueSortAdd(open,n,d_n);
        end
    end
end
Return EmptyList();
```

Algorithm 1: The A* algorithm for the path-planning with the real travel cost $g()$ calculated on the traversability map, and the heuristic travel cost $h()$ calculated with the Euclidian distance.

6 Multi-Robot Exploration and Communication

In our previous work, an exploration approach was demonstrated which made a selection between a small number of frontiers, based on the information gain available beyond those frontiers [17]. Each robot may calculate the balance between movement costs and information gain for itself and for each of its teammates. Consequently an optimal robot-frontier assignment can be determined in which robots assign themselves to frontiers, and no frontier is explored by more than one robot. The result is efficient, fully autonomous multi-robot exploration.

Including communication success into this exploration approach [8] means that robots will prefer frontiers from which they can likely communicate to frontiers that are likely to be out of range. However, frontiers that are out of

[3] The implementation provided by Rasto Novotny is used. This implementation is published for download in December 2005 on `http://www.developerfusion.com/code/5052/priority-queue-net/`.

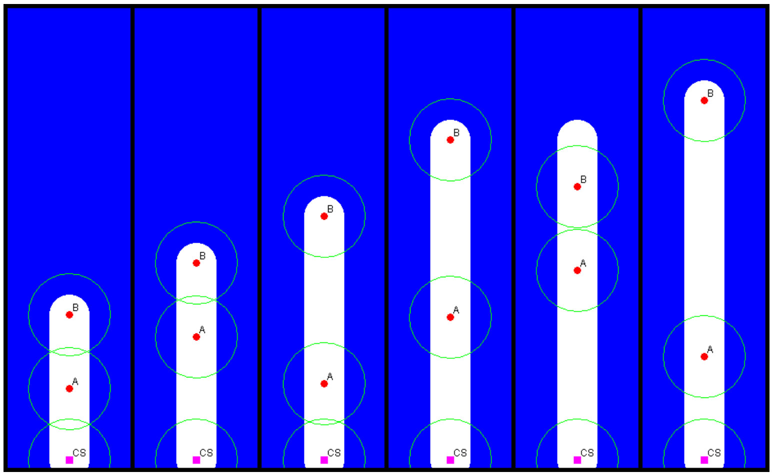


Fig. 3. A possible communication relay strategy for large environments. Green circles indicate communication ranges, white indicates free space as sensed by the agents. Initially agents A and B set out to explore. When they reach the full extent of the communication chain, A breaks its link with the ComStation and follows B. After enough new information is attained, A assumes the role of relay and returns to the ComStation, while B continues to explore. After enough new information is acquired, B returns to rendezvous with A, which in turn relays the information back while B turns around to continue with exploration.

range are just as important to explore, and require additional consideration. Two possible solutions are:

1. to visit the area of interest, and then physically return to the ComStation to transmit the new knowledge
2. to visit the area of interest, and then transmit the new knowledge to the ComStation via multi-hop communication using team members

The second solution described above may be implemented by using a role-based approach: robots may dynamically become *explorers* or *relays* as part of the ongoing exploration effort. A relay need not be stationary – it may follow an exploring robot for some time, and periodically return to transmit new knowledge to the ComStation (see Fig. 3). It is hoped that the ensuing team behavior allows for exploration deep into the environment, even in areas that are far beyond the team's initial range.

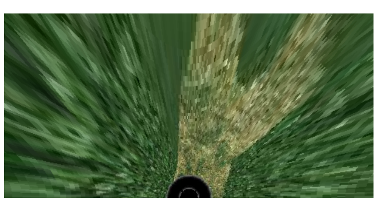
7 Free Space detection

Camera images can be used for teleoperation and to detect victims. Camera images can also be used as independent information to detect free space. Range scanners, which are typically used as primary means to detect free space, are active sensors which have a limited range and a limited field of view. Additionally, active sensors are relatively heavy and consume considerable amounts of energy, which makes them less attractive for small mobile robots. In contrast, the limit of a visual sensor range can lie as far as the horizon and omnidirectional vision methods can provide a 360° view of the environment. A method to identify free space based on visual sensor data could well expand the environment observation quality of a rescue robot.

As part of this year's effort, two visual free space classifiers were trained using a laser-range scanner as reference [9]. The same laser-range data, acquired elsewhere on the map, is used as ground truth to test the precision and recall of these free space classifiers. This training and testing was performed both in simulation (see Fig. 7) and on a collected dataset.

Fig. 4. The maze in the DM-compWorldDay1_250 map.

The result is a precision of 0.93 and a recall of 0.86 in the detection of the free space for the Gaussian Mixture Model classifier with optimal settings. Which such a high precision and recall, the free space can be clearly distinguished from obstacles, as illustrated in Fig. 5.



(a) Bird-eye view image from the maze.

(b) Free space detected by Gaussian Mixture Model classifier.

Fig. 5. Bird-eye view image from the maze and the free space detection result.

This free space classifier can be learned by robots equipped with both a camera and a laser range scanner and distributed wirelessly to other robots equipped with only a camera, such as the AirRobot [10]. The validity of this approach is demonstrated by using a dataset collected with our Nomad Super Scout II robot.

8 Conclusion

This paper summarizes improvements in the robot control environment of the Amsterdam Oxford Joint Rescue Team since RoboCup 2008 in Suzhou. This progress was demonstrated at the Latin American Robotics Competition, where the first prize was won with fully autonomous exploration. At the German Open 2009 competition the teleoperation test was won thanks to the application of AirRobots, the mapping test was won based on the robust WSM algorithm and the deployment test was won thanks to the autonomous exploration algorithm. More important, the progress is well documented in a number of publications in international robotics conferences.

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