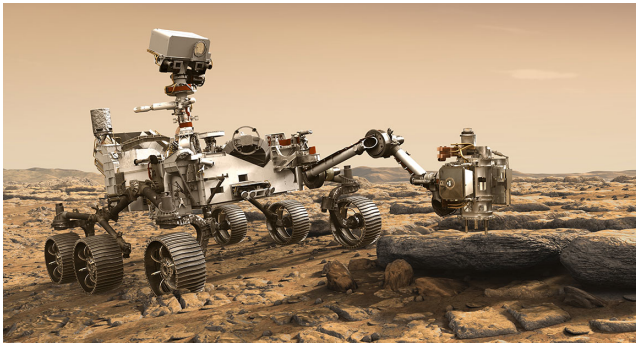
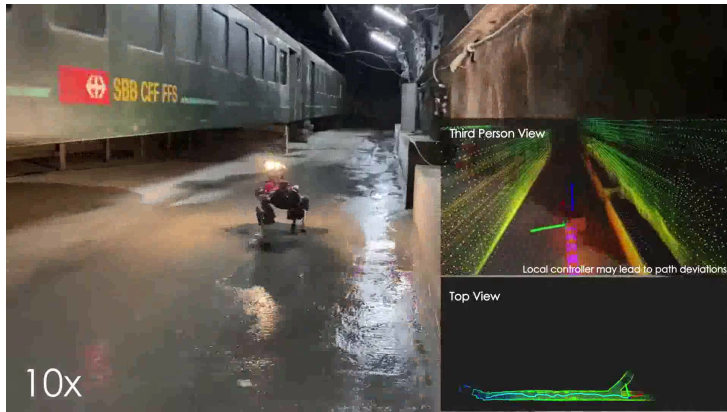


Robotic exploration

Vojtěch Vonásek

Department of Cybernetics
Faculty of Electrical Engineering
Czech Technical University in Prague





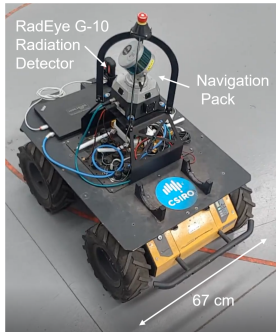
<https://www.youtube.com/watch?v=P3uT4gHEFHw>

Finding precious metals, water sources, etc.



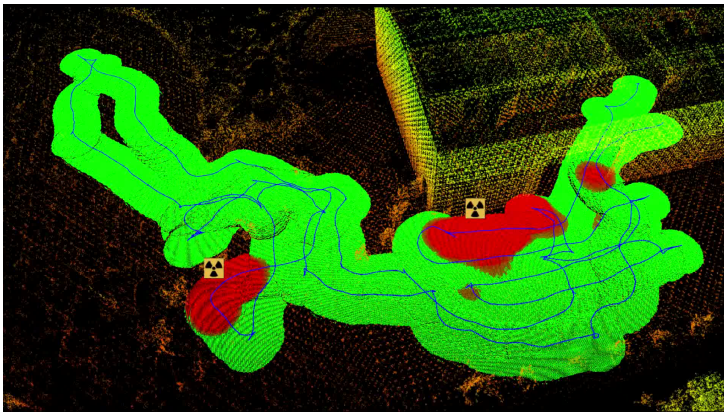
Finding and rescuing people in debris

Source: robohub.org



Mapping radioactive zones

• Groves, K.; Hernandez, E.; West, A.; Wright, T.; Lennox, B. Robotic Exploration of an Unknown Nuclear Environment Using Radiation Informed Autonomous Navigation. *Robotics* 2021, 10, 78.



www.youtube.com/watch?v=Hj7xt7isOWc

Mapping radioactive zones

- Groves, K.; Hernandez, E.; West, A.; Wright, T.; Lennox, B. Robotic Exploration of an Unknown Nuclear Environment Using Radiation Informed Autonomous Navigation. *Robotics* 2021, 10, 78.

Exploration

- *the activity of searching and finding out about something* (Cambridge English dictionary)
- *... is a trip, but it's more than just a vacation — it's going somewhere to examine and discover new things* (vocabulary.com)

Robotic exploration

- *use a robot to maximize knowledge over a particular area*
 - Is there a precious metal? Where are the victims? Is there a radioactivity?
- Fundamental problem of robotics
- Single robot vs. multi-robot exploration
- Practical problem needed in many applications

Reactive

- measure, evaluate, act, measure, evaluate, . . .
- not optimal (e.g., time/energy consuming)
- can lead to cycles



Decision-based

- build a model of the environment
- make decision using the model
- more efficient, can be optimized
- extra effort to make the model of the environment



How to represent/model environment?

- Many approaches
- Model should always be selected according given application

Low-level data

- Raw sensor data (e.g. LIDAR values, images)
- Neural network models (weights+topologies), learned policies (Reinforcement learning), rosbag
- File formats: (txt,bin,SQL,HDF,...)
- They are specific to given task/environment
- Hard to interpret by humans
- Poor generalization



```
-6.30069 -3.44217 5.68828 -0.436222 -0.0131647 0 -6.81021 -3.46388 5.68797 -0.53538 -0.000235049 0 2 2654
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-6.69381 -3.5577 5.69085 -0.77459 0.038554 0 -6.65811 -3.59264 5.6931 -0.77459 0.0514837 0 2 2654
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-6.55118 -3.69728 5.70372 -0.77459 0.0902727 0 -6.51561 -3.73209 5.70855 -0.77459 0.103202 0 2 2654
-6.51561 -3.73209 5.70855 -0.77459 0.103202 0 -6.48009 -3.76685 5.71402 -0.77459 0.116132 0 2 2654
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-6.44463 -3.80156 5.72013 -0.77459 0.129062 0 -6.40922 -3.83621 5.72689 -0.77459 0.141991 0 2 2654
-6.40922 -3.83621 5.72689 -0.77459 0.141991 0 -6.37388 -3.87079 5.73429 -0.77459 0.154921 0 2 2654
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-6.30173 -3.93792 5.75099 -0.675262 0.18078 0 -6.26195 -3.96671 5.7603 -0.577836 0.19371 0 2 2654
-6.26195 -3.96671 5.7603 -0.577836 0.19371 0 -6.21967 -3.99144 5.77024 -0.480656 0.20664 0 2 2654
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-5.98604 -4.04857 5.82941 0.000974371 0.271288 0 -5.93804 -4.04624 5.84311 0.0963339 0.284218 0 2 2654
```


Example of models of environments

Low-level data

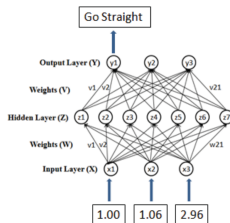
- Raw sensor data (e.g. LIDAR values, images)
- Neural network models (weights+topologies), learned policies (Reinforcement learning), rosbag
- File formats: (txt,bin,SQL,HDF,...)
- They are specific to given task/environment
- Hard to interpret by humans
- Poor generalization



Database Structure															Browse Data	Edit Pragmas	Execute SQL
Table: runs															Filter in any column...		
id	erime	anner	ate	t_sc	solutio	ph_motio	graph_states	memory	on_clean	n_diff	ution_len	n_sec	n_smooth	solve			
F...	Filter	Filter	F...	F...	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Fil...	Filter	Filter			
1	1	1	1	0	1	1	3155	3156	29.8047	0.0	0.0	24.0663	240	25934.3			
2	2	1	1	0	1	1	3224	3225	30.9531	0.0	0.0	26.4969	265	29009.0			
3	3	1	1	0	1	1	3380	3381	31.7266	0.0	0.0	24.9994	250	25997.5			
4	4	1	1	0	1	1	2912	2913	32.5	0.0	0.0	26.6361	267	29869.0			
5	5	1	1	0	1	1	2164	2165	33.0156	0.0	0.0	17.6915	178	16955.1			
6	6	1	1	0	1	1	3802	3803	34.0469	0.0	0.0	26.1314	262	29102.3			
7	7	1	1	0	1	1	2527	2528	35.0781	0.0	0.0	25.2687	253	29115.4			
8	8	1	1	0	1	1	4053	4054	35.5938	0.0	0.0	18.2766	183	18188.8			
9	9	1	1	0	1	1	2476	2477	36.8828	0.0	0.0	17.0454	171	17560.3			
10	10	1	1	0	1	1	3034	3035	36.8828	0.0	0.0	18.4882	185	19938.6			
11	11	1	2	0	1	1	7441	7442	38.6836	0.0	0.0	29.6971	14	13.4658			
12	12	1	2	0	1	1	11815	11816	41.0039	0.0	0.0	22.5842	11	15.7426			
13	13	1	2	0	1	1	2010	2010	42.2242	0.0	0.0	20.1056	14	15.1027			

Low-level data

- Raw sensor data (e.g. LIDAR values, images)
- Neural network models (weights+topologies), learned policies (Reinforcement learning), rosbag
- File formats: (txt,bin,SQL,HDF,...)
- They are specific to given task/environment
- Hard to interpret by humans
- Poor generalization



T. Zhao and Y. Wang, "A neural-network based autonomous navigation system using mobile robots", International Conference on Control Automation Robotics & Vision, 2012

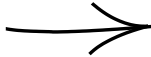
Processed data

- Interpreted sensor data (e.g. obstacles, walls, ground, free-space, ...)
- Good generalization
- Can be easily interpreted by humans



```

-0.003584 0.00092978 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
-0.436222 -0.0131647 0 -6.81021 -3.46308 5.68797 -0.53318 -0.000239049 0 2 2854
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-0.190799 0.245429 0 -6.03423 -4.04831 5.81632 -0.0947537 0.258399 0 2 2854
-0.0947537 0.258399 0 -5.96004 -4.04897 5.82841 -0.000974129 0.271108 0 2 2854
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```

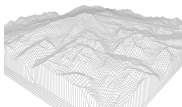
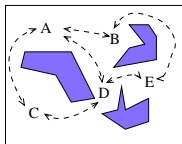
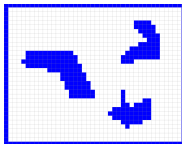


- These models are simply known as maps

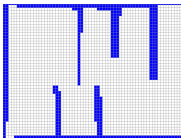
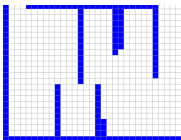
- Map is the model of the world/environment
- Many types (2D/3D, grid, polygonal, ...)
- Usually contain geometric features (e.g. walls, ground, obstacles)
- Necessary for decision making (e.g. planning, navigation, inspections, ...)

Properties

- Supported operations (e.g. merging maps, adding new information, deleting obstacles, ...)
- Computational complexity of these procedures
- Memory requirements
- Precision
- Robustness (with respect to numerical errors)
- There is no 'universal' map
- One should always choose a map suitable for the given application



- 2D or 3D array (grid) of cells
- Binary maps: 0/1 (obstacle, free spaces)
- Probability: 0–1 (0=free space, 1=obstacle)
 - occupancy grid
 - often used for integration of sensor data, SLAM
- ✓ Metric information (distance/angle/area ...)
- ✓ Easy implementation
- ✓ Efficient search for obstacle cells, nearest obstacle cell, ...
- ✓ Straightforward update of cells & map merging
- ✓ Integration of data from different sensors
- ✗ High memory requirements
 - depends on environment size & map resolution
 - practical limit to 2D and 3D environments



5VdzKHreB_s

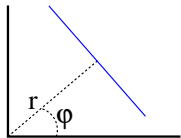


Source: Robotic Dataset repository (Radish): fr097

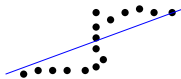
- 2D worlds, suitable for structured indoor scenes
- Obstacles are represented by lines
- Compact way to store range-sensor measurements (x_i, y_i)

$$\tan 2\varphi = \frac{-2 \sum_i (\bar{x} - x_i)(\bar{y} - y_i)}{\sum_i ((\bar{y} - y_i)^2 - (\bar{x} - x_i)^2)}$$

$$r = \bar{x} \cos \varphi + \bar{y} \sin \varphi$$

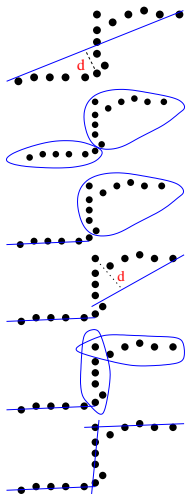


- Can be extended for 3D planes
- ✓ Memory efficient, easy to process, metric information
- ✓ Fast tests for collisions, point location
- ✗ What if data points are generated by multiple linear structures?
 - How many lines are needed?
 - How to assign points to individual lines?



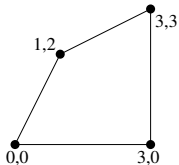
Split and merge recursive approach

- 1 Compute line for a given set of points $(x_1, y_1) \dots (x_n, y_n)$
 - 2 Find the most distant point i from the line, its distance is d
 - 3 If d is smaller than a threshold, return line
 - 4 Otherwise, split points to two groups $(x_1, y_1), \dots (x_i, y_i)$ and $(x_{i+1}, y_{i+1}), \dots (x_n, y_n)$ and proceed recursively on each group
- Easy to implement, fast
 - The result is not optimal (does not minimize square distances of points from lines)

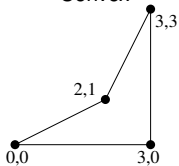


• D.H. Douglas, T.K. Peucker: Algorithms for the reduction of the number of points required to represent a line or its caricature, Cdn. Cartogr. 10(2), 1973

- 2D worlds
- Obstacle is represented by polygon
 - $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$
- (x_i, y_i) are vertices
- The map is the collection of obstacles
- Simple polygon: does not intersect itself, no holes
- Polygons with holes: contour + one or more holes
- ✓ Memory efficient, easy to process, metric information
- ✓ Fast tests for collisions, point location
- ✗ Numerical stability of (some) algorithms
- ✗ Number of vertices can dramatically grow if map is built from (unfiltered) sensor data



Convex



Non-convex



Polygon from Lidar



Map $\sim 100 \times 5$ m, ~ 1 k vertices

What kind of maps are using humans?

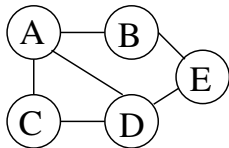
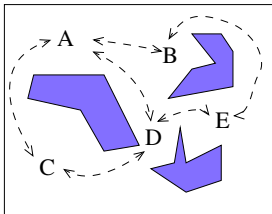
- grid, occupancy grid, polygonal, line-map . . . ?

What kind of maps are using humans?

- grid, occupancy grid, polygonal, line-map ... ?



- Abstract map, lack of geometric and metric features
- Represented by a graph
 - Vertices are (distinguishable) places
 - Edges connecting places between the robot can navigate
- Scalable, used for high-level planning



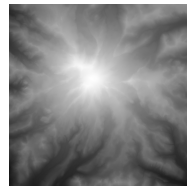
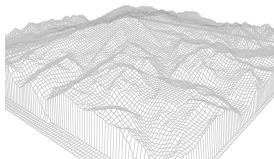
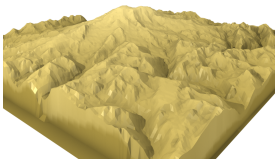
- Abstract map, lack of geometric and metric features
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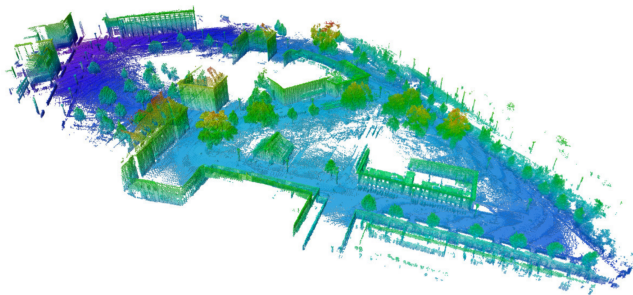
- Abstract map, lack of geometric and metric features
- Represented by a graph
 - Vertices are (distinguishable) places
 - Edges connecting places between the robot can navigate
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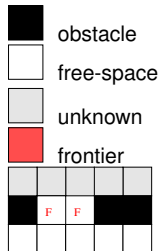
- Elevation (2.5D grid map): each cell describes altitude



- Pointclouds, octomap



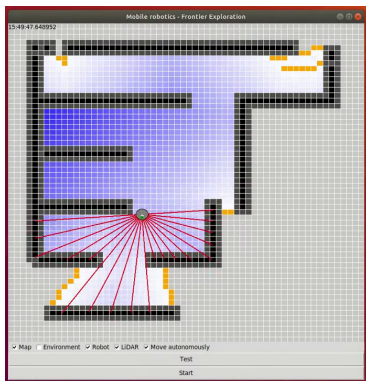
- A variant of grid map
 - **Known cell**: value of $c_i \geq 0$ (contains prob. of being occupied)
 - **Unknown cell**: value of $c_i = -1$
- Interpretation of known cells:
 - Free-space (no obstacle): $p(\text{occupied}) < T$
 - Obstacle: $p(\text{occupied}) > T$
 - where T is a threshold, e.g. 0.8
- **Frontier**: the border between known and unknown regions
- **Frontier cell**
 - is a free-space cell that is incident with an unknown cell
 - it may not be reachable



- Robot is gathering (desired) information in an environment
- Search & rescue, searching for Barbie, precious metals, etc.
- We used model of the environment (map) to do it efficiently
- Often used solution: SLAM (Simultaneous localization and mapping)

Challenges

- How to represent the map
- How to update it
- How to localize
- How to determine where to go
- How to get there



<https://www.youtube.com/watch?v=B-dSyKx4Fsc>

Principle: use a frontier as a temporary goal

- 1 Identify frontiers in the map
- 2 Filter out unreachable frontiers (if any)
- 3 Select a frontier and go there
- 4 Goto 1 until no frontier exists

Notes

- Unreachable frontiers detected using path planning
 - Consider navigating to the closest frontier
 - Consider detecting frontiers during movement of the robot
 - Detection of frontiers should be fast
- YAMAUCHI, B., et al. Frontier-based exploration using multiple robots. Agents. 1998; 47-53.
- KEIDAR, Matan; KAMINKA, Gal A. Ecient frontier detection for robot exploration. The International Journal of Robotics Research, 2014, 33.2: 215-236.



- obstacle
- free-space
- unknown
- frontier

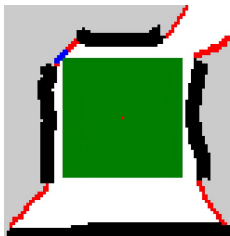
- Image-based
 - Convert occupancy grid to binary image, run edge detection
- Wavefront Frontier Detector (WFD) (👁️ Keidar)
 - Graph-search method to detect frontiers
 - Run BFS from actual position of the robot
 - This BFS explores only free cells (i.e., also frontier cells)
 - Run another BFS if frontier cell is visited
 - The second BFS explores only frontier cells
 - The goal of second BFS is to extract all cells belonging to the actually detected frontier
- Both BFS share open/close list



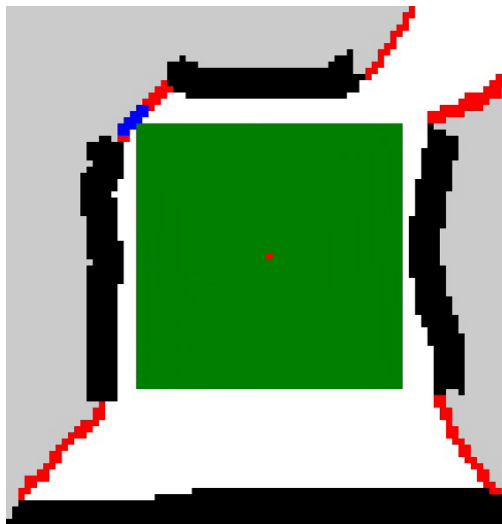
- obstacle
- free-space
- unknown
- frontier

- 👁️ YAMAUCHI, B., et al. Frontier-based exploration using multiple robots. Agents. 1998; 47-53.
- 👁️ KEIDAR, Matan; KAMINKA, Gal A. Ecient frontier detection for robot exploration. The International Journal of Robotics Research, 2014, 33.2: 215-236.

```
1 O = { robot position }  
2 while |O| ≥ 0 do  
3   pos = O.pop()           // open list for main BFS  
4   mark pos as known  
5   for c in neighbors(pos) do  
6     if c is explored or c is obstacle then  
7       continue  
8     if c is frontier cell then  
9       Of = {c} // open list for second BFS  
10      while |Of| ≥ 0 do  
11        posf = Of.pop()  
12        mark posf as known  
13        for cf in neighbors(posf) do  
14          if cf is not frontier cell or cf is known  
15            then  
16              continue  
17            Of.push(cf)  
18        else  
19          O.push(c)
```

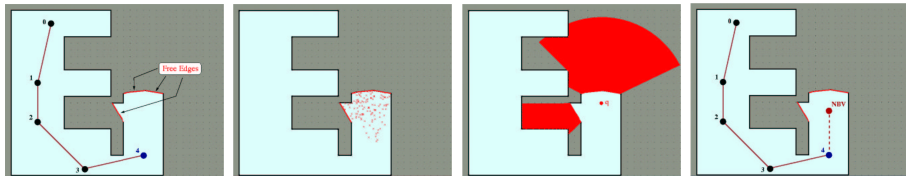


- pos, pos_f = coordinates of a cell in grid, e.g. (x, y)
- robot position = actual position of the robot in the grid
- O : open list for main BFS search — free cells
- O_f : open list for exploration of individual frontiers — frontier cells



Several ideas to get better (faster) exploration

- Consider cost of path to the frontier for frontier selection
- Consider how much area is 'behind' the frontier (aka 'view'), visit the most promising frontiers first → next best view approach
- Combination of above



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