Improved Sampling-based Motion Planning Methods

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Lecture 06

B4M36UIR – Artificial Intelligence in Robotics

Overview of the Lecture

- Part 1 – Improved Sampling-based Motion Planning Methods
  - Optimal Motion Planners
  - Rapidly-exploring Random Graph (RRG)

Part I

Part 1 – Improved Sampling-based Motion Planning Methods

Efficient Sampling–Based Motion Planning

- PRM and RRT are theoretically probabilistic complete
- They provide a feasible solution without quality guarantee
  Despite that, they are successfully used in many practical applications
- In 2011, a study of the asymptotic behaviour has been published
  It shows, that in some case, they converges to a noon-optimal value with a probability 1.
- Based on the study, new algorithms have been proposed: RRG and optimal RRT (RRT^{star})

Sampling-based algorithms for optimal motion planning
Sertac Karaman, Emilio Frazzoli
International Journal of Robotic Research, 30(7):846–894, 2011.

RRT and Quality of Solution

- RRT provides a feasible solution without quality guarantee
  Despite of that, it is successfully used in many practical applications
- In 2011, a systematical study of the asymptotic behaviour of randomized sampling-based planners has been published
  It shows, that in some cases, they converge to a non-optimal value with a probability 1.

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http://sertac.scripts.mit.edu/rrtstar

RRT and Quality of Solution 1/2

- Let Y_i^{RRT} be the cost of the best path in the RRT at the end of iteration i.
- Y_i^{RRT} converges to a random variable

$$\lim_{i\to\infty} Y_i^{RRT} = Y_\infty^{RRT}.$$

- The random variable Y_∞^{RRT} is sampled from a distribution with zero mass at the optimum, and

$$Pr[Y_\infty^{RRT} > c^*] = 1.$$

Karaman and Frazzoli, 2011

- The best path in the RRT converges to a sub-optimal solution almost surely.

RRT and Quality of Solution 2/2

- RRT does not satisfy a necessary condition for the asymptotic optimality
  - For $0 < R < \inf_{q\in\mathcal{Q}_{goal}} ||q - q_{init}||$, the event $\{\lim_{n\to\infty} Y_n^{RTT} = c^*\}$ occurs only if the k-th branch of the RRT contains vertices outside the R-ball centered at q_{init} for infinitely many k.
    See Appendix B in Karaman&Frazzoli, 2011
- It is required the root node will have infinitely many subtrees that extend at least a distance ϵ away from q_{init}
  The sub-optimality is caused by disallowing new better paths to be discovered.

Rapidly-exploring Random Graph (RRG)

RRG Algorithm

Vstup: q_{init}, number of samples n
Výstup: $G = (V, E)$

$V \leftarrow \emptyset$; $E \leftarrow \emptyset$;
for $i = 0, \ldots, n$ **do**
  $q_{rand} \leftarrow$ SampleFree;
  $q_{nearest} \leftarrow$ Nearest($G = (V, E), q_{rand}$);
  $q_{new} \leftarrow$ Steer($q_{nearest}, q_{rand}$);
  if CollisionFree($q_{nearest}, q_{new}$) **then**
    $\mathcal{Q}_{near} \leftarrow$ Near($G = (V, E), q_{new}, \min\{\gamma_{RRG}(\log(\mathrm{card}(V))/\mathrm{card}(V))^{1/d}, \eta\}$);
    $V \leftarrow V \cup \{q_{new}\}$; $E \leftarrow E \cup \{(q_{nearest}, q_{new}), (q_{new}, q_{nearest})\}$;
    foreach $q_{near} \in \mathcal{Q}_{near}$ **do**
      if CollisionFree(q_{near}, q_{new}) **then**
        $E \leftarrow E \cup \{(q_{rand}, u), (u, q_{rand})\}$;
return $G = (V, E)$;

Proposed by Karaman and Frazzoli (2011). Theoretical results are related to properties of Random Geometric Graphs (RGG) introduced by Gilbert (1961) and further studied by Penrose (1999).

RRG Expansions

- At each iteration, RRG tries to connect new sample to the all vertices in the r_n ball centered at it.
- The ball of radius

$$r(\mathrm{card}(V)) = \min\left\{\gamma_{RRG}\left(\frac{\log(\mathrm{card}(V))}{\mathrm{card}(V)}\right)^{1/d}, \eta\right\}$$

where
  - η is the constant of the local steering function
  - $\gamma_{RRG} > \gamma^*_{RRG} = 2(1 + 1/d)^{1/d}(\mu(\mathcal{C}_{free})/\xi_d)^{1/d}$
    - d – dimension of the space;
    - $\mu(\mathcal{C}_{free})$ – Lebesgue measure of the obstacle–free space;
    - ξ_d – volume of the unit ball in d-dimensional Euclidean space.
- The connection radius decreases with n
- The rate of decay ≈ the average number of connections attempted is proportional to $\log(n)$

RRG Properties

- Probabilistically complete
- Asymptotically optimal
- Complexity is $O(\log n)$

(per one sample)

- Computational efficiency and optimality
  - Attempt connection to $\Theta(\log n)$ nodes at each iteration;

    in average

    - Reduce volume of the "connection" ball as $\log(n)/n$;
    - Increase the number of connections as $\log(n)$.

Other Variants of the Optimal Motion Planning

- **PRM*** – it follows standard PRM algorithm where connections are attempted between roadmap vertices that are within connection radius r as a function of n

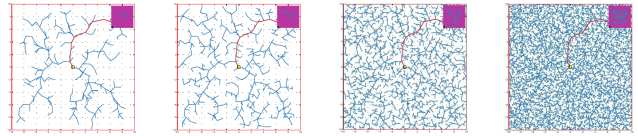
$$r(n) = \gamma_{PRM}(\log(n)/n)^{1/d}$$

- **RRT*** – a modification of the RRG, where cycles are avoided

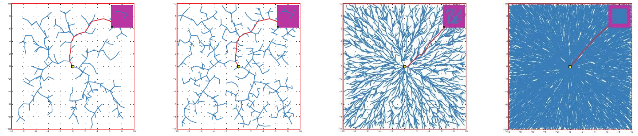
  A tree version of the RRG

  - A tree roadmap allows to consider non-holonomic dynamics and kinodynamic constraints.
  - It is basically RRG with "rerouting" the tree when a better path is discovered.

Example of Solution 1/2



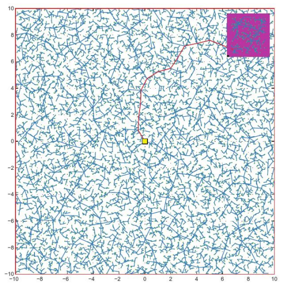
RRT, n=250 RRT, n=500 RRT, n=2500 RRT, n=10000



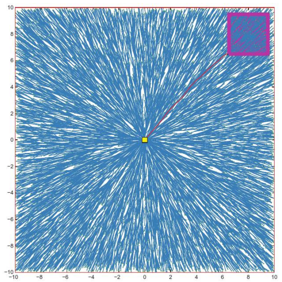
RRT*, n=250 RRT*, n=500 RRT*, n=2500 RRT*, n=10000

Karaman & Frazzoli, 2011

Example of Solution 2/2



RRT, n=20000



RRT*, n=20000

Overview of Randomized Sampling-based Algorithms

Algorithm	Probabilistic Completeness	Asymptotic Optimality
sPRM	✔	✘
k-nearest sPRM	✘	✘
RRT	✔	✘
RRG	✔	✔
PRM*	✔	✔
RRT*	✔	✔

Notice, k-nearest variants of RRG, PRM, and RRT* are complete and optimal as well.*

Summary of the Lecture

Topics Discussed

- Optimal sampling-based motion planning
- Rapidly-exploring Random Graph (RRG)

- Next: Robotic information gathering and Data collection planning