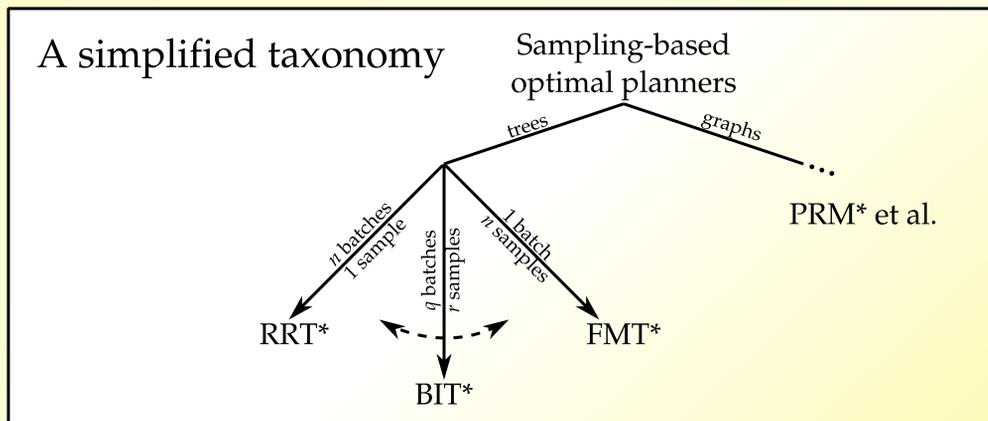


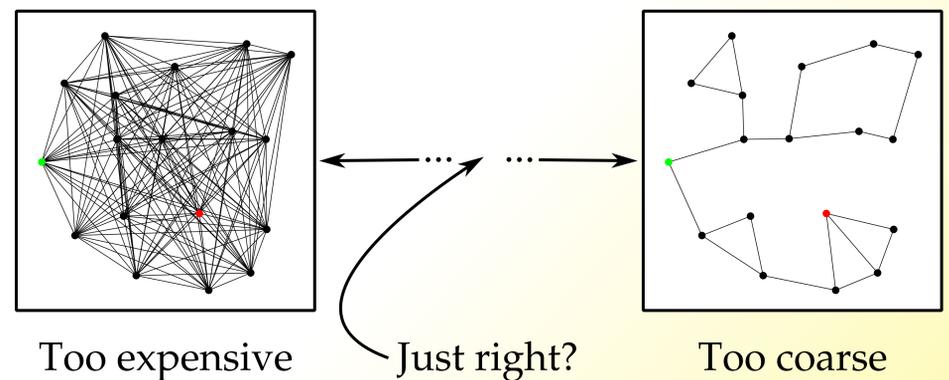
BIT*: Sampling-based Optimal Planning via Batch Informed Trees

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1 In optimal planning, sampling-based techniques can be viewed as the search of an implicit random graph embedded in the problem space. The samples define the graph vertices, but what edges should we consider? The complete graph is too expensive to search and low-degree graphs are too coarse to give good solutions. Random geometric graph (RGG) theory provides lower bounds on the necessary graph complexity for probabilistic graph properties like almost-sure connectedness and asymptotic optimality.



Implicit sample-based graphs

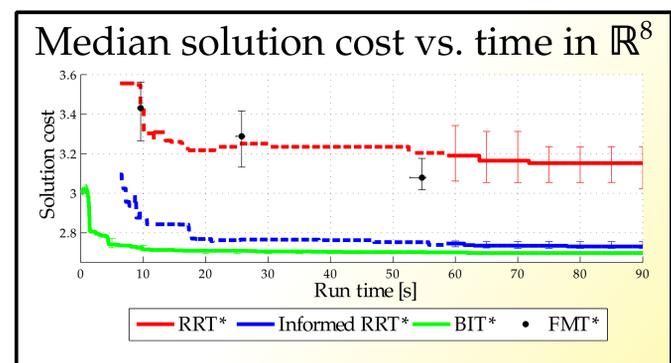
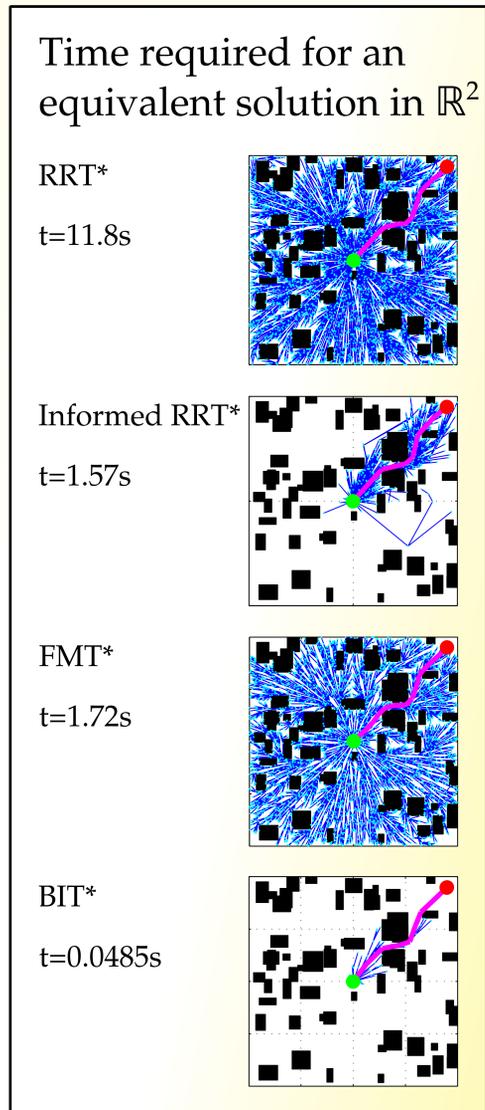
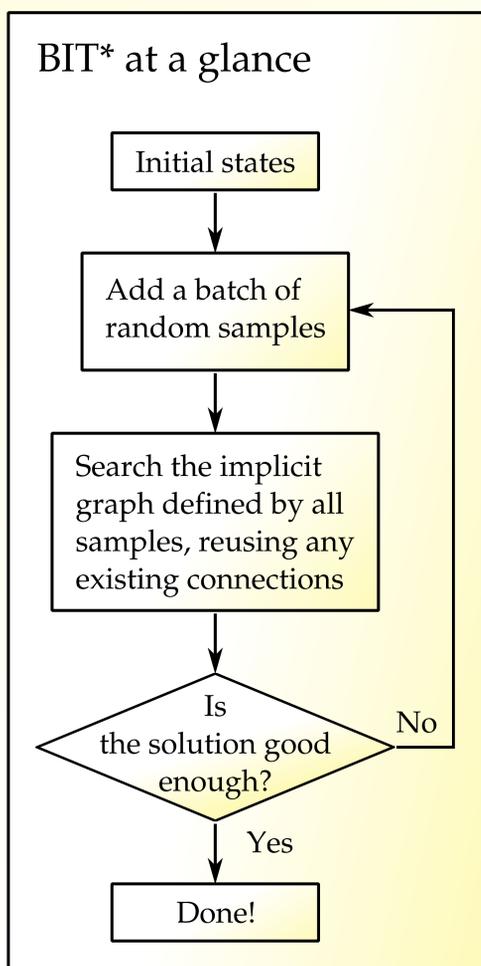


2 RRT* uses the results of RGGs to search a combination of online and nearest-neighbour graphs to provide an anytime asymptotically optimal planner; however, its search is *random*. FMT* orders its search through the nearest-neighbour graph in terms of increasing cost to come; however, it is *not anytime*. BIT* unifies and extends these techniques to develop an ordered anytime asymptotically optimal planner that can be focused with an appropriate heuristic.

3 BIT* accomplishes this by iteratively searching the implicit nearest-neighbour RGGs defined by *multiple* batches of samples. This allows it to perform an *ordered search* in an *anytime* manner. With a suitable heuristic, this prioritizes high-quality initial solutions. During refinement this also limits the search to only the subdomain of the planning problem that could contain a better solution.

4 From the results of Karman and Frazzoli (2011) it can be shown that BIT* is probabilistically complete and asymptotically optimal. Is it possible to use the results of Hart et al. (1968) to also evaluate its *probabilistic efficiency*?

5 BIT* was compared in simulation to existing sampling-based optimal planners for a variety of state-dimensions. While the results are preliminary, BIT* consistently outperformed existing algorithms in the computational time necessary to find solutions of equivalent cost, with the difference increasing with state dimension.



6 More information

- Preprint (<http://arxiv.org>): [arXiv:1405.5848 \[cs.RO\]](https://arxiv.org/abs/1405.5848)
- Email: jon.gammell@utoronto.ca
- Web: <http://asrl.utias.utoronto.ca>



7 Related work

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- P. E. Hart, N. J. Nilsson, and B. Raphael. A formal basis for the heuristic determination of minimum cost paths. *TSSC*, 4(2):100–107, Jul. 1968.
- S. Karaman and E. Frazzoli. Sampling-based algorithms for optimal motion planning. *IJRR*, 30(7):846–894, 2011.
- L. Janson and M. Pavone. Fast marching trees: a fast marching sampling-based method for optimal motion planning in many dimensions. *ISRR*, Dec. 2013.
- J. D. Gammell, S. S. Srinivasa, and T. D. Barfoot. Informed RRT*: Optimal sampling-based path planning focused via direct sampling of an admissible ellipsoidal heuristic. *IROS*, to appear. 2014. [arXiv:1404.2334 \[cs.RO\]](https://arxiv.org/abs/1404.2334).