Cloud RRT*: Sampling Cloud based RRT*

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Abstract

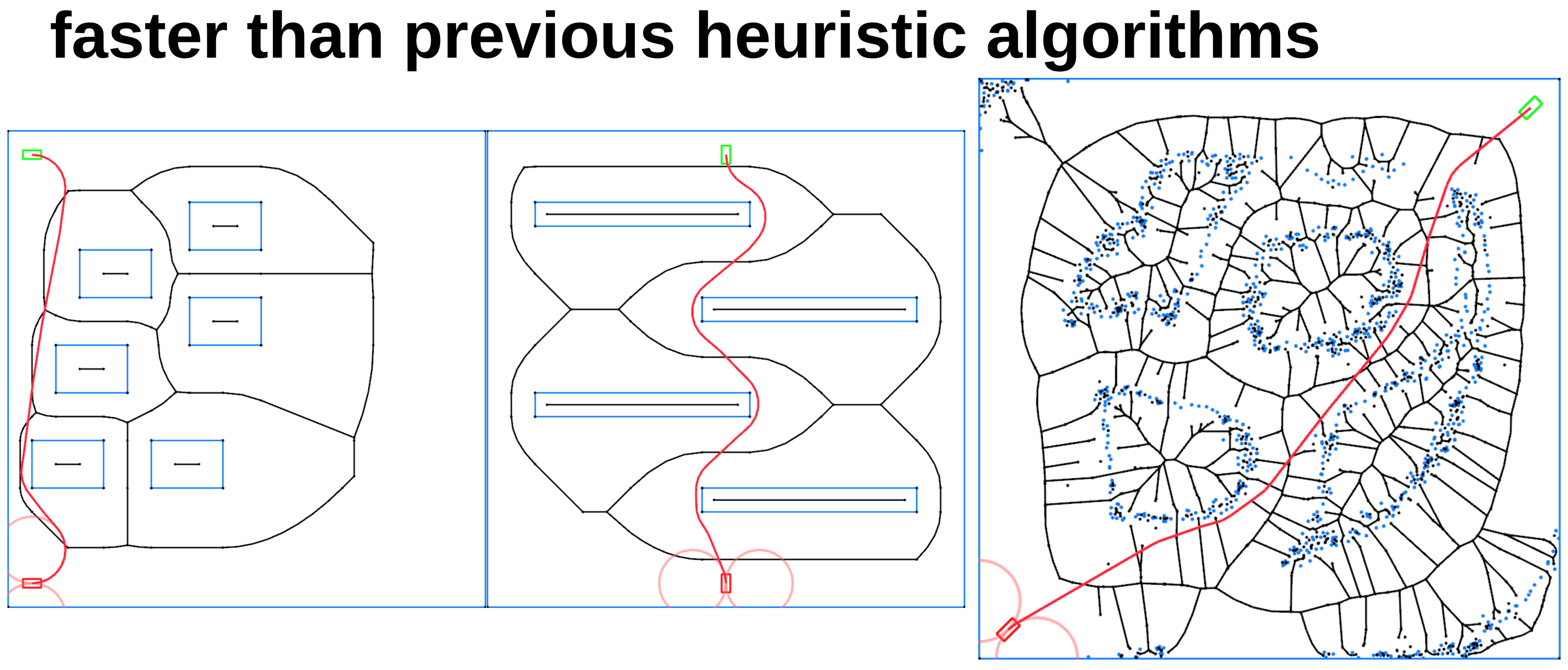
We present a novel biased sampling technique, Cloud RRT*, for efficiently computing high-quality collision-free paths while maintaining the asymptotic convergence to the optimal solution. Our method uses a dedicated data structure named sampling cloud for allocating samples on promising regions. Sampling cloud consists of a set of spheres containing a portion of the C-space, which is initialized by sphere expansion and workspace analysis based on the Generalized Voronoi Graph. We then update our sampling cloud to refine the current best solution, while maintaining the global sampling distribution for exploring understudied other homotopy classes to achieve a rapid convergence speed toward the optimal solution. We have applied our method to a 2D motion planning problem with kinematic constraints, and achieve better performance up to three times, over prior methods in a robust manner.

Our Goals

- **Achieve a rapid convergence speed toward the optimal solution**
- **Maintain the global sampling distribution for less explored area (alleviate the dilemma between exploration and exploitation)**

Main Results

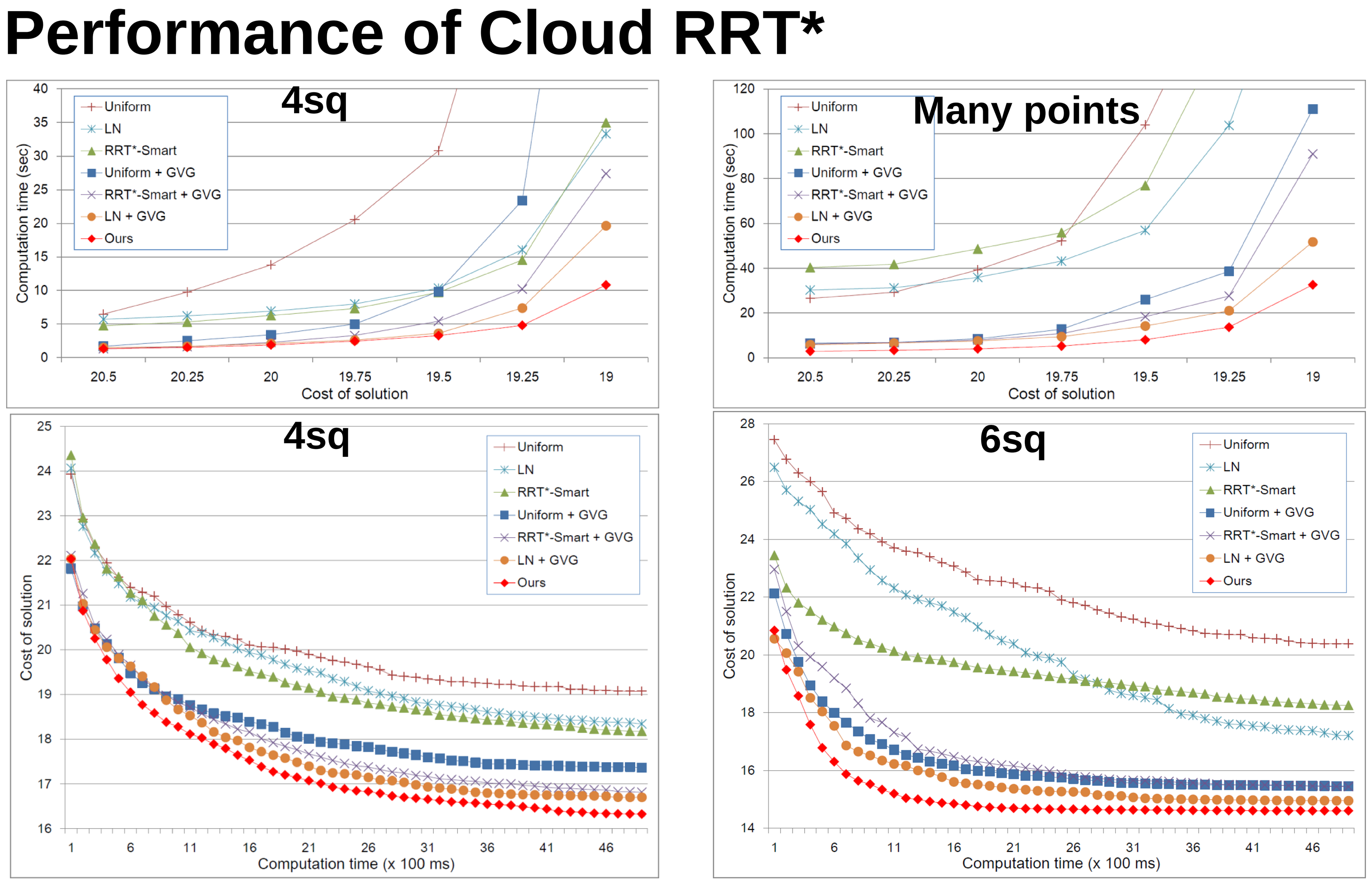
- **Improve the convergence speed**
- **Provide an order of magnitude improvement against standard RRT* and also up to 3 times faster than previous heuristic algorithms**



Benchmark(6sq, 4sq, many points)

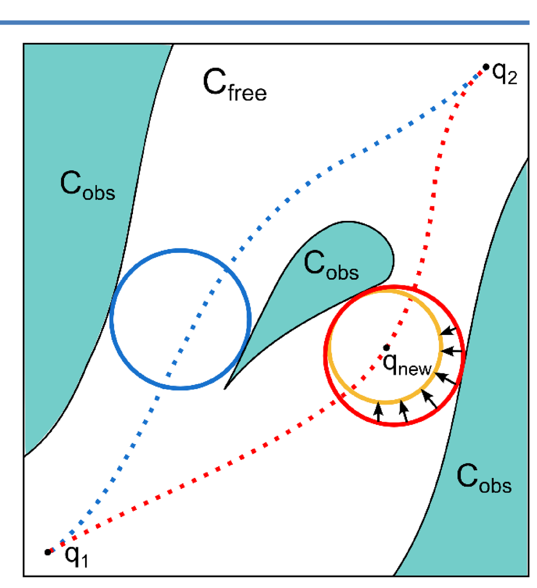
Tested on 3 different 2D environment, using Dubins vehicle model
Normalized optimal cost of each solution is less than 14.48, 15.58, 18.9, respectively(Left to the Right).

Performance of Cloud RRT*



Key Idea

The given motion planning problem can be viewed as a chain of optimization problem in the sampling cloud. To be specific, we assume each small problem represented by smaller sampling sphere, as a single convex problem and then update & prune sampling cloud to narrow down search space for rapid convergence rate.



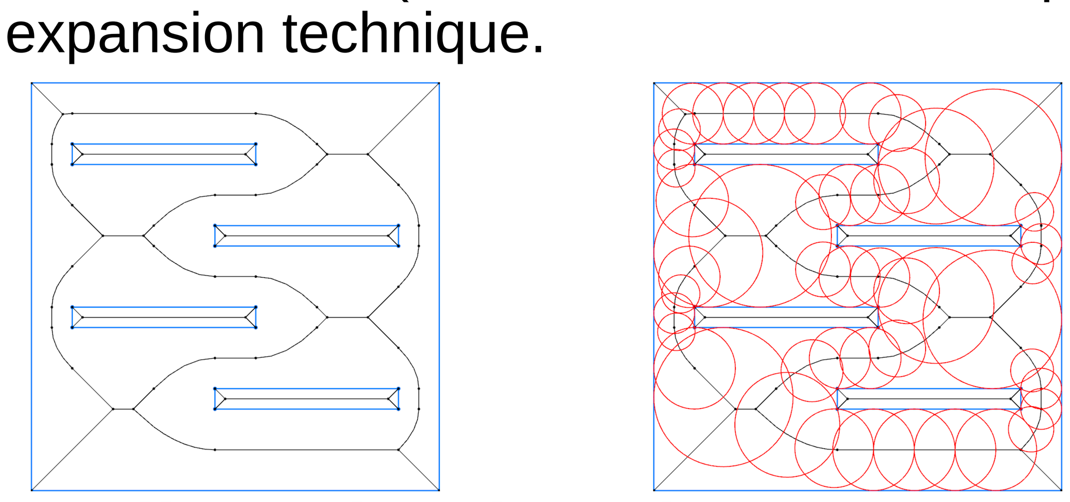
Approaches

Sampling Cloud and GVG-Initialization

Sampling cloud is a set of spheres which represents a subset of C-space.

Sampling cloud $Xs = \{x \mid (Proj(x) \in s) \cap (x \in X)\}$, where
$x \in X$: a configuration in C-space X
$s \in Xs$: a sphere in Sampling cloud Xs
$Proj(\cdot)$: a projection function from the C-space to workspace

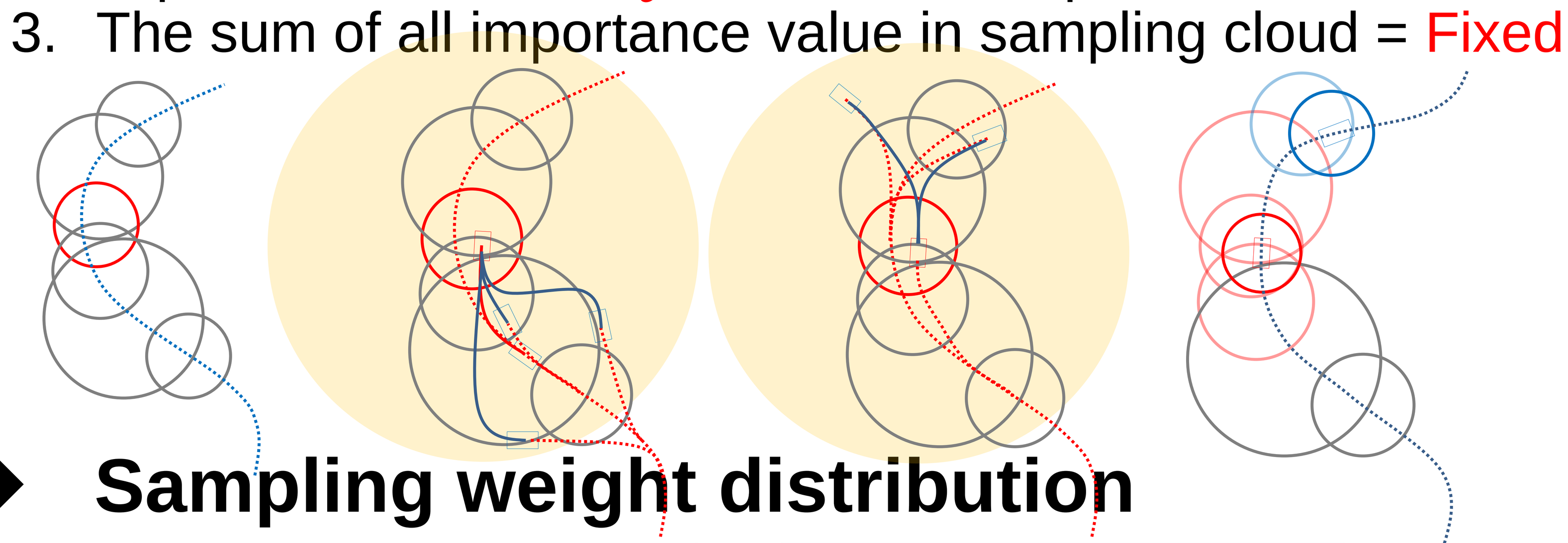
A sampling sphere in sampling cloud has Center position, Radius, Orientation range $[\varphi - \theta, \varphi + \theta]$, where a main orientation φ, and deviation value θ and importance value, a relative probability to be sampled. Our sampling cloud initialization uses GVG(Generalized Voronoi Graph)-guided sphere expansion technique.



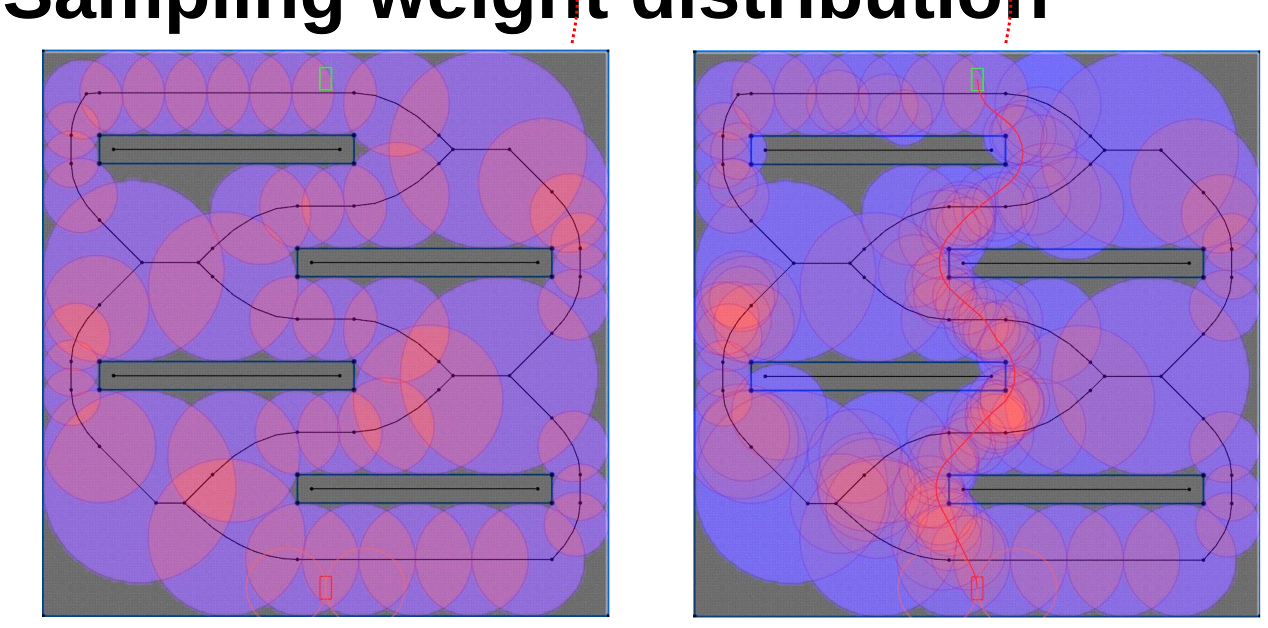
Sampling Cloud Update

We update our sampling cloud whenever a new milestone appears. A milestone is a set of configurations in the new best solution, but not included in all the prior old solutions.

1. For each configuration of milestone m, we find all sampling spheres in sampling cloud that include the configuration, denoted by S_c.
2. Generate a new sphere associated with center position(position of m), main orientation(orientation of m), deviation(θ_n), radius and importance value. Some of the importance value of S_c to that of new sphere.
3. The sum of all importance value in sampling cloud = Fixed



Sampling weight distribution



Initial(left) and updated(right) sampling weight distribution

Homotopy property of sampling sphere
For a holonomic robot, All of the path through any configurati-on within a collision-free sphere are homotopic to each other, and the distribution of their cost satisfies Lipschitz continuity.