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

Approaches
◆ Sampling Cloud and GVG-Initialization
Sampling cloud is a set of spheres which represents a subset of C-space.
\[
\text{Sampling cloud } X_s = \{ x \in \text{C-space} | \text{Pr}(x) \in s \in X \} \text{, where } x \in X \text{ : a configuration in C-space } X \\
S \subseteq X_s \text{ : a sphere in Sampling cloud } X_s \\
\text{Pr}(x) \text{ : a projection function from the C-space to workspace}
\]
A sampling sphere in sampling cloud has Center, Radius, Orientation range \([\phi - \delta, \phi + \delta]\), where a main orientation \(\phi\), and deviation value \(\theta\) 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(\(m\)), 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

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.