MORRF*: Sampling-based Multi-Objective Motion Planning

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Introduction
Motivation
- Multiple objectives in planning paths
- Conflicts between objectives
- Incomparability between objectives

Solution
Interactively select a path from a Pareto-optimal set

Related work
MOEA-D decomposes a multi-objective problem into a set of single-objective subproblems.

In finding M Pareto-optimal paths in a K-objective problem, the forest consists of M subproblem trees and K reference trees.

For a given weight \( \lambda^m \), a single-objective subproblem can be created by:
- Weighted-sum \( \sum_{k=1}^{K} \lambda^m_k c_k(x) \)
- Tchebycheff \( \max_{1 \leq k \leq K} (\lambda^m_k c_k(x) - z_k^{stop}) \)

In the forest,
- All trees have the same vertices.
- Trees might have different edges, which are determined by corresponding single objective.

Weighted-sum approach
- The solutions of all the subproblem trees constitute the Pareto-optimal solutions.

Tchebycheff approach
- Reference trees provide the estimated Utopia reference vector.
- The solutions of all the subproblem trees constitute the Pareto-optimal solutions.

Simulation
The measurement of the performance includes:
- Pareto optimality - All the paths are Pareto-optimal.
- Approximation capability - The set of paths is diverse.

Three approaches can be compared visually in a two-dimensional fitness space.

Two approaches of MORRF* are then compared in a map with obstacles. The existence of obstacles leads to discontinuity in the fitness space.

Similar results are obtained with three objectives, which are visualized in three dimensions.

As in the 2-D case, solutions from both approaches approximate the Pareto front, but the Tchebycheff approach shows better diversity.