MORRF*: Sampling-based Multi-Objective Motion Planning

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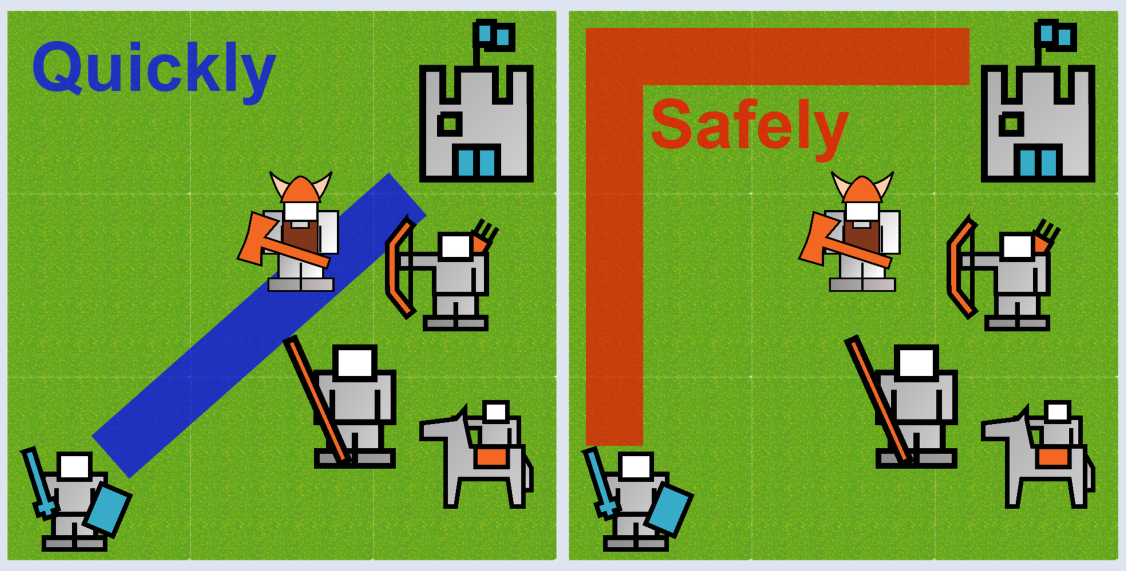
Introduction

Motivation

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

Solution
Interactively select a path from a Pareto-optimal set



Goal
Find a set of Pareto-optimal (non-dominated) paths given multiple objectives

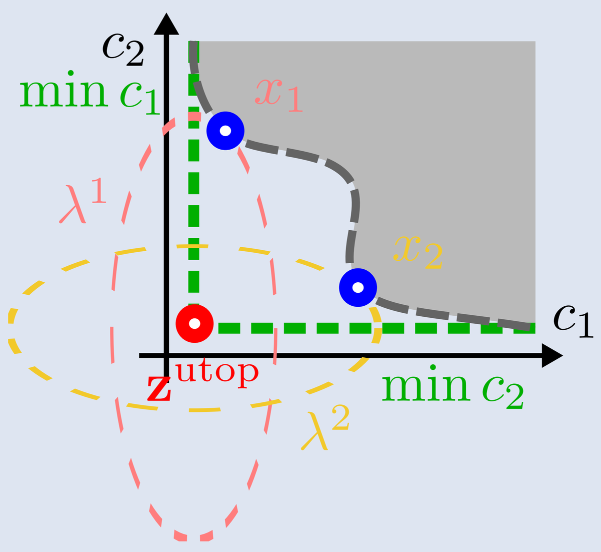
Challenges

- Nonconvexity of planning space
- Discontinuity caused by obstacles
- Inconsistency in path lengths and shapes
- Accumulation of fitness along path

Related work

MOEA-D

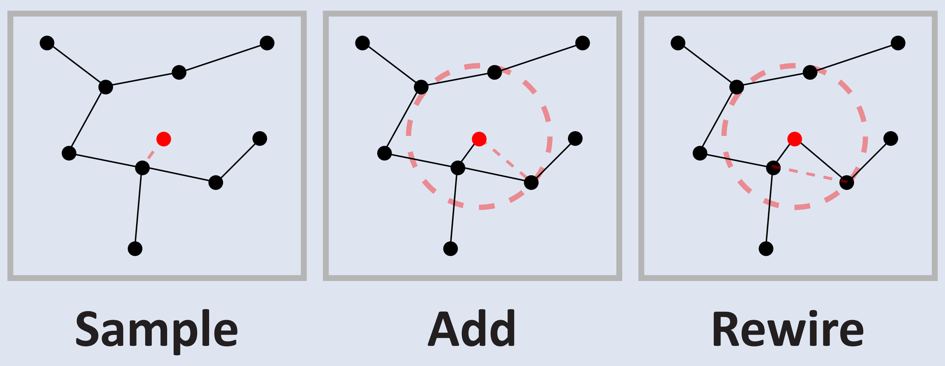
MOEA-D decomposes a multi-objective problem into a set of single-objective subproblems.



- Generate a set of M diffferent weights $\{\boldsymbol{\lambda}^1, \cdots, \boldsymbol{\lambda}^M\}$
- Create corresponding single objective subproblems using:
  - Weight $\boldsymbol{\lambda}^m$
  - Utopia reference vector $\mathbf{z}^{utop}$
- Solve each subproblem
- The resultant set of solutions approximates the Pareto-optimal set

RRT*

RRT* connects points sampled randomly from the state space and generates a tree for path planning.
The tree converges to an optimal structure such that any path from the root to a vertex is optimal.

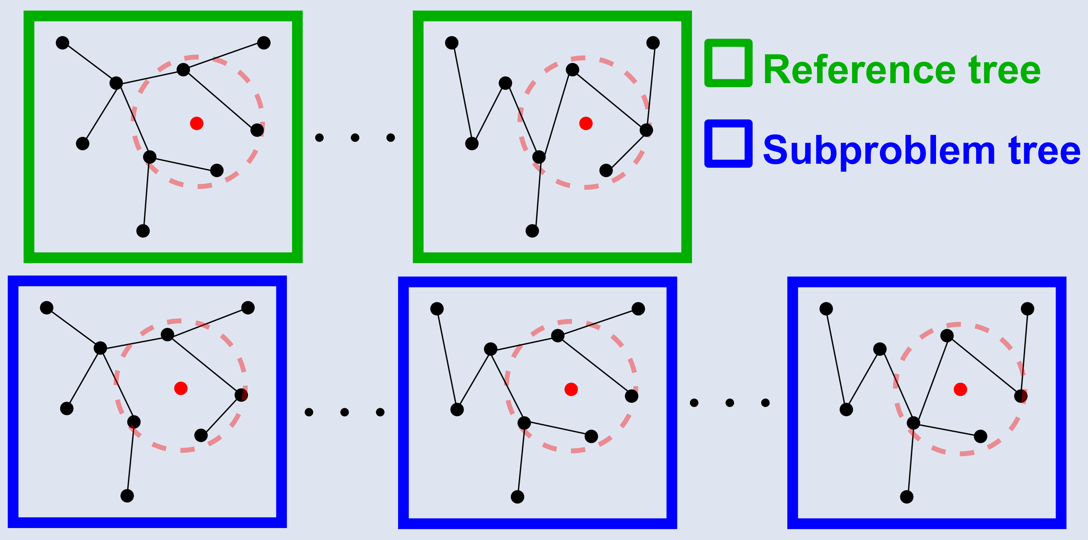


- simple (=efficient)
- high degrees of freedom
- probabilistically complete
- asymptotically optimal

The solution from RRT* asymptotically converges to the optimal.

MORRF*

MORRF* stands for **Multi-Objective Rapidly-exploring Random Forest***.



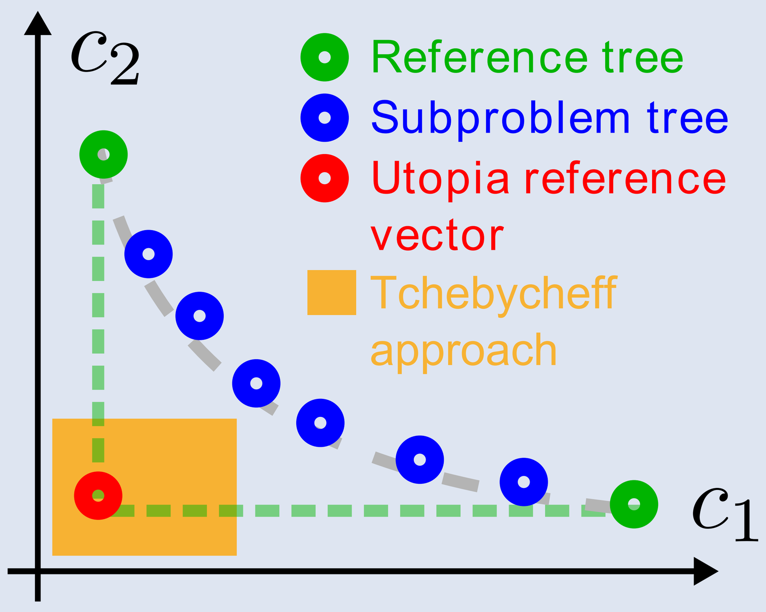
In finding M Pareto-optimal paths in a K-objective problem, the forest consists of M subproblem trees and K reference trees.

For a given weight $\boldsymbol{\lambda}^m$, a single-objective subproblem can be created by:

- **Wegithed-sum** $\sum_{k=1}^{K} \lambda_k^m c_k(x)$
- **Tchebycheff** $\max_{1 \leq k \leq K} \left(\lambda_k^m | c_k(x) - z_k^{utop} | \right)$

In the forest,

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

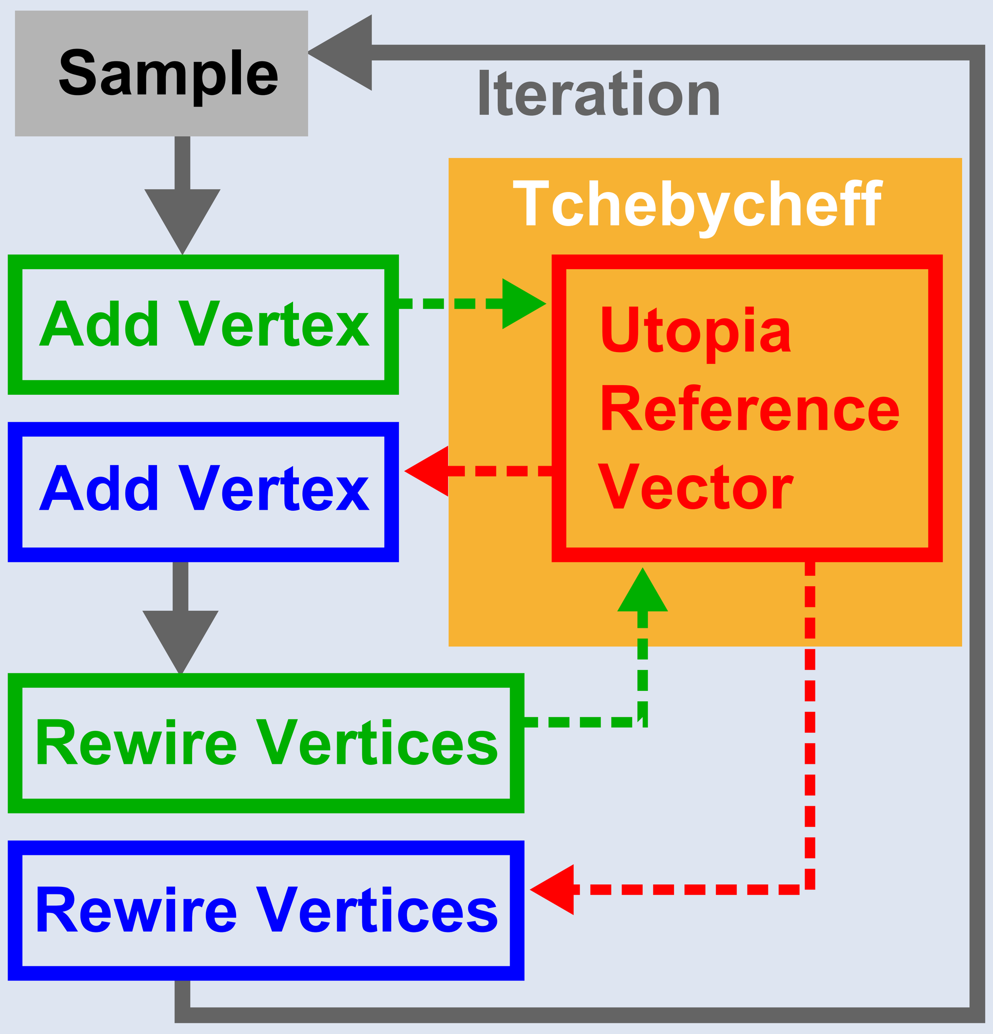


Weighted-sum approach

- 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.

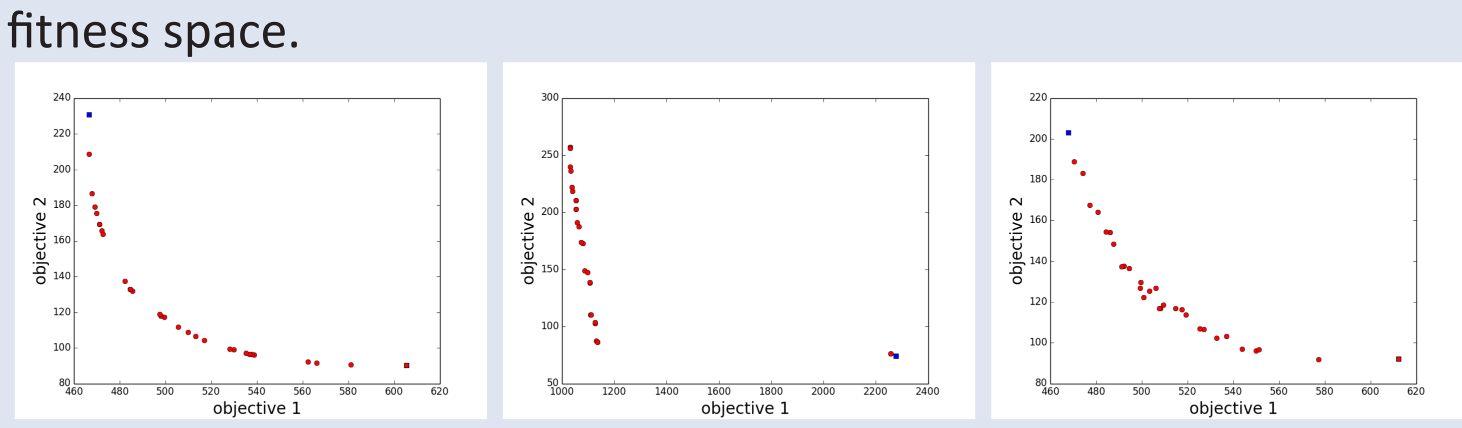


Simulation

The measurement of the performance includes

- **Pareto optimality** - All the paths are Pareto-optimal.
- **Approximation capability** - The set of paths is diverse.

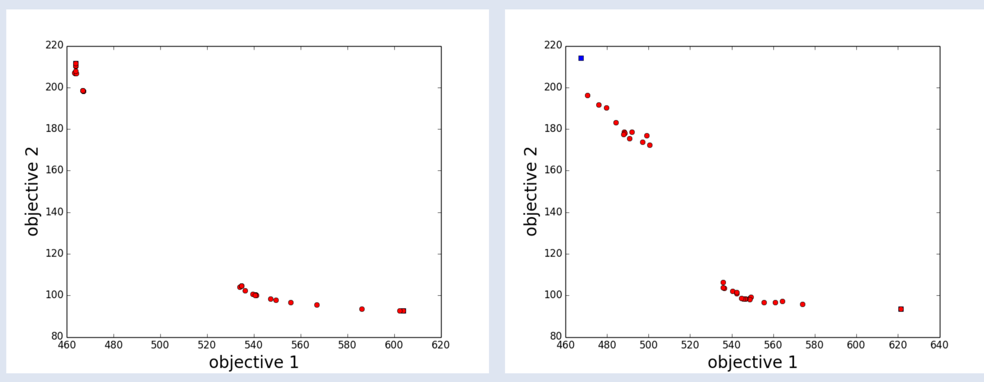
Three approaches can be compared visually in a two-dimensional fitness space.



Weighted sum (MORRF*) | NSGA-II | Tchebycheff (MORRF*)

The solutions from NSGA-II are far from the Pareto front, because the convergence is slower. The solutions from the Weighted-sum approach and the Tchebycheff approach of MORRF* converge to the Pareto-optimal set. The solutions from the Tchebycheff approach show better diversity.

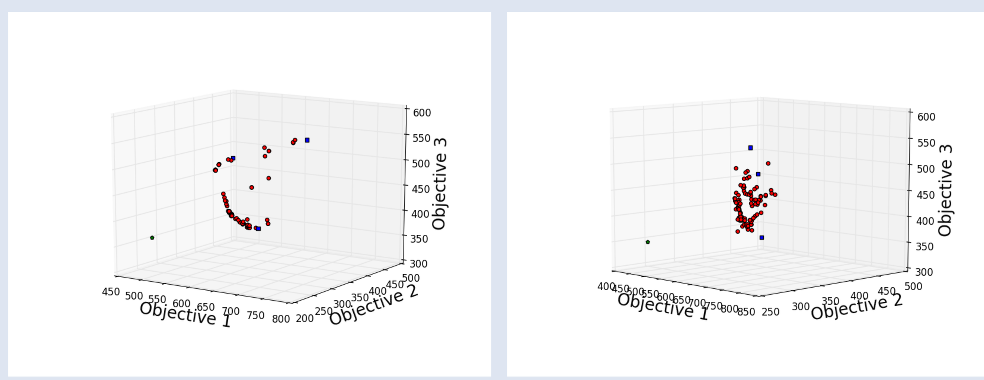
Two approaches of MORRF* are then compared in a map with obstacles. The existence of obstacles leads to discontinuity in the fitness space.



Weighted sum (MORRF*) | Tchebycheff (MORRF*)

Both approaches generate Pareto-optimal solutions, but the Tchebycheff approach yields better diversity.

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



Weighted sum (MORRF*) | Tchebycheff (MORRF*)

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