

Multi-Robot Team Formation Under Uncertain Environment

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Introduction

Multi-robot team formation under uncertain environment arises in a wide variety of application scenarios like patrolling, automated transport of goods, environmental monitoring and surveillance.

We consider a pipeline surveillance problem with a team of quadrotors (see Fig.1). Given a route of a pipeline with known distance (L in Eq.1) and a set of quadrotors with different operation cost (c_i in Eq.1) and ability of travelling (l_i in Eq.1) which is random variable, **we need to form a team of quadrotors** from the given set to detect leakage such that **in any realization the quadrotor team covers the pipeline with at least a pre-specified probability while the overall operation cost is minimized.**

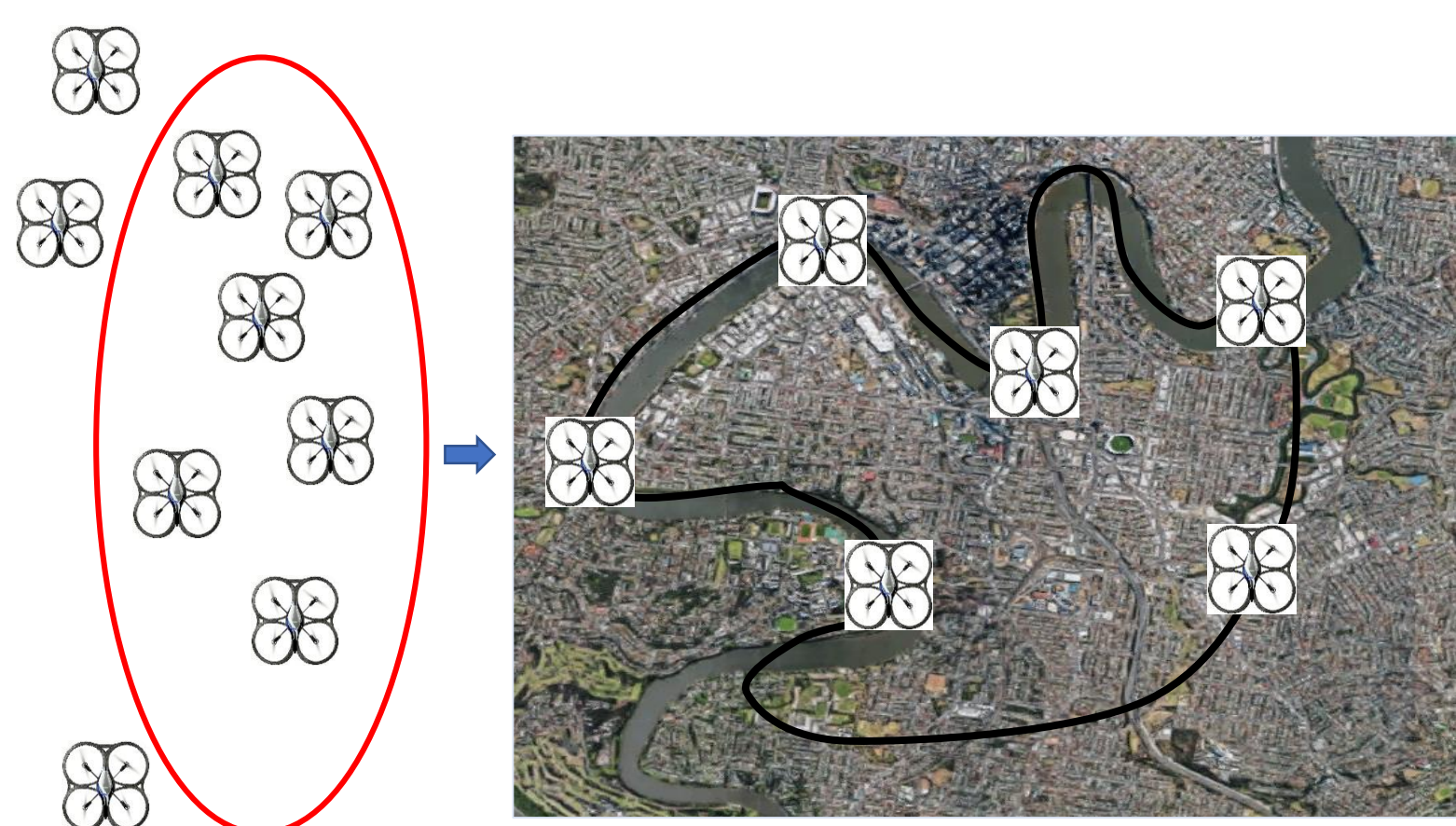


Fig. 1. A pipeline should be traversed by robots with random travel distances. The goal is to select a team of robots from the given set to minimize the total cost such that the route is traversed with probabilistic guarantee.

Problem Formulation

This problem is a chance-constrained knapsack problem (CC-KAP):

$$\begin{aligned} \min \quad & \sum_{i=1}^n c_i f_i \\ \text{s.t.} \quad & \mathbb{P} \left(\sum_{i=1}^n l_i f_i \geq L \right) \geq p \\ & f_i \in \{0, 1\}, \quad \forall i = 1, \dots, n \end{aligned} \quad (1)$$

- The solution is a vector where each entry f_i is a binary decision variable indicating that a robot is selected when $f_i = 1$.
- The chance constraint guarantees that **under any realization of the random travel distance, the selected team covers the route with at least a pre-specified probability p .**
- The chance constraint is equivalent to a deterministic constraint $\sum_i \mu_i f_i - C \sqrt{\sum_i \sigma_i^2 f_i} \geq L$ where C is a constant determined by p .

To solve CC-KAP, we solve a sequence of deterministic problems, called risk-averse knapsack problem (RA-KAP).

$$\begin{aligned} \min \quad & \sum_{i=1}^n c_i f_i \\ \text{s.t.} \quad & \sum_{i=1}^n \mu_i f_i - \lambda \sqrt{\sum_{i=1}^n \sigma_i^2 f_i} \geq L' \\ & f_i \in \{0, 1\}, \quad \forall i = 1, \dots, n \end{aligned} \quad (2)$$

This problem is essentially a **deterministic 0-1 knapsack problem** where the travel distances of robots are linear combinations of means (μ_i) and variances (σ_i^2), λ is risk-averse parameter and the route length is L' .

Geometric Interpretation

- The problem is analyzed on a 2D variance-mean plane (see Fig.2) where x-axis, y-axis represent the sum of variances and means of the selected robots respectively.
- Any robot team can be represented as a point on variance-mean plane.
- **The optimal solution is the point in the non-convex feasible region (above blue parabola in Fig.2a) with the highest objective value.**
- **The optimal solution of CC-KAP is the optimal solution of a RA-KAP with appropriate choice of (λ, L') .**
- Thus, the problem is converted to a two-dimensional search (λ, L') on variance-mean plane.

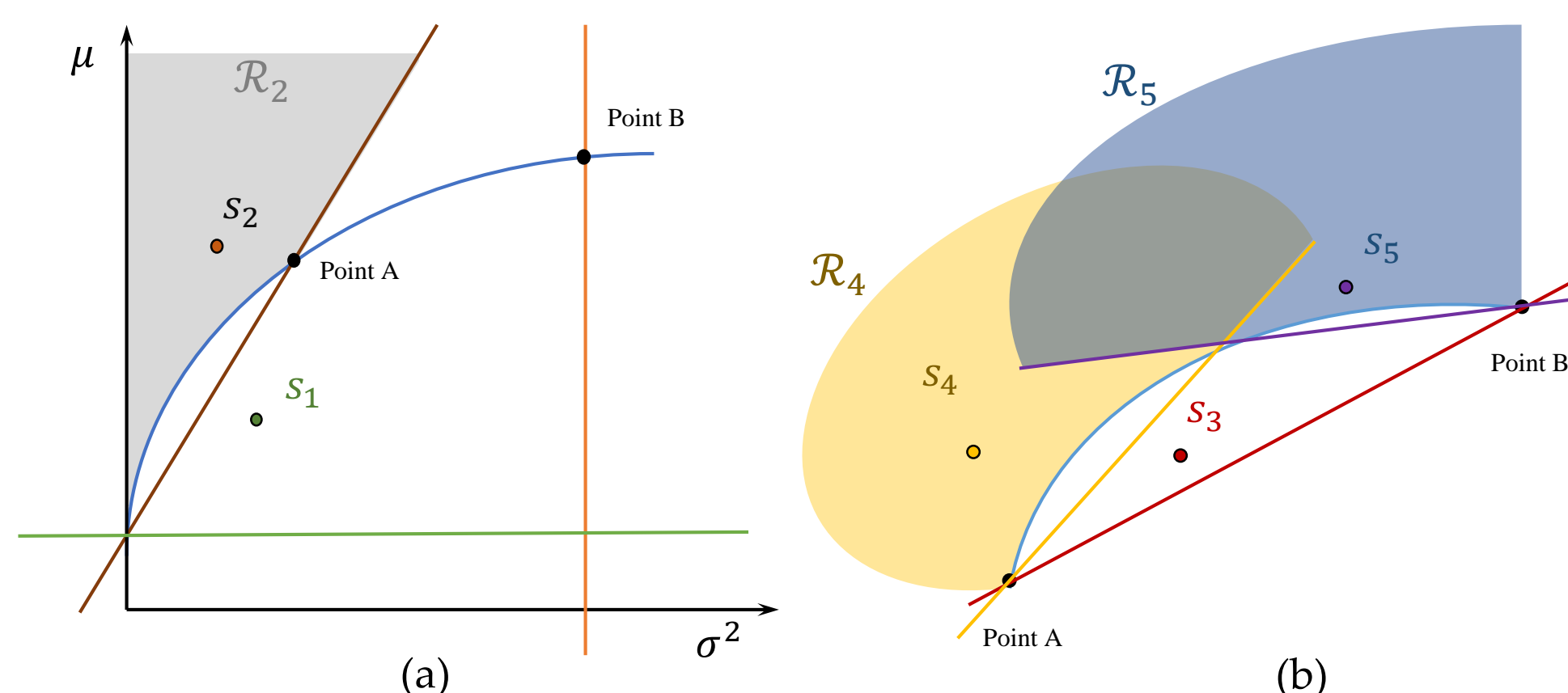


Fig. 2. Illustration of our two-step algorithm. The feasible region of CC-KAP (\mathcal{R}) is the non-convex space above the parabola. Fig.(a) illustrates the first step, where we find a feasible solution of CC-KAP (s_2) which is optimal in the intersection region \mathcal{R}_2 . Fig.(b) zooms in the remaining feasible region $\mathcal{R} \setminus \mathcal{R}_2$. It illustrates the second step, where we find several feasible solutions, (s_4, s_5) that are optimal in the intersection region of CC-KAP and the corresponding RA-KAP, ($\mathcal{R}_4, \mathcal{R}_5$) such that the union of those intersection regions and the region in the first step, \mathcal{R}_2 covers the feasible region of CC-KAP, e.g. $\mathcal{R} \subseteq \cup_{i \in \{2,4,5\}} \mathcal{R}_i$.

Algorithm

We develop a two-step algorithm to solve the CC-KAP optimally:

1. Solve a sequence of RA-KAPs by methodically increasing λ that controls the slope of the straight line until the optimal solution of a RA-KAP (s_2 in Fig. 2a) is feasible to CC-KAP.
2. Solve RA-KAPs by methodically changing parameters (λ, L') that control the slope and y-intercept of the straight line. If the optimal solution of a RA-KAP is feasible to CC-KAP, we obtain a solution that is

optimal in the intersection of feasible regions of CC-KAP and RA-KAP, e.g., $\mathcal{R}_4, \mathcal{R}_5$ in Fig.2b. The **procedure terminates** when the intersection regions corresponding to those feasible solutions, e.g., $\mathcal{R}_4, \mathcal{R}_5$, cover the remaining feasible region of CC-KAP at the end of the first step, i.e., $\mathcal{R} \setminus \mathcal{R}_2$, in Fig.2a.

Simulation Results

Simulations are performed based on randomly generated means and variances for travel distance capacity of each robot. We count the number of RA-KAPs solved which influences the efficiency and scalability of our algorithm.

- Fig. 3 shows the scalability of our algorithm as a function of the number of robots varying from 10 to 100. The results shown are obtained from 100 randomly generated scenarios.
 - The average numbers of RA-KAP solved is constant (< 3) irrespective of the number of robots while the maximum number is at most 7 (see Fig.3).
- **Our algorithm is scalable with the number of robots or variances of travel distances (not shown in poster).**

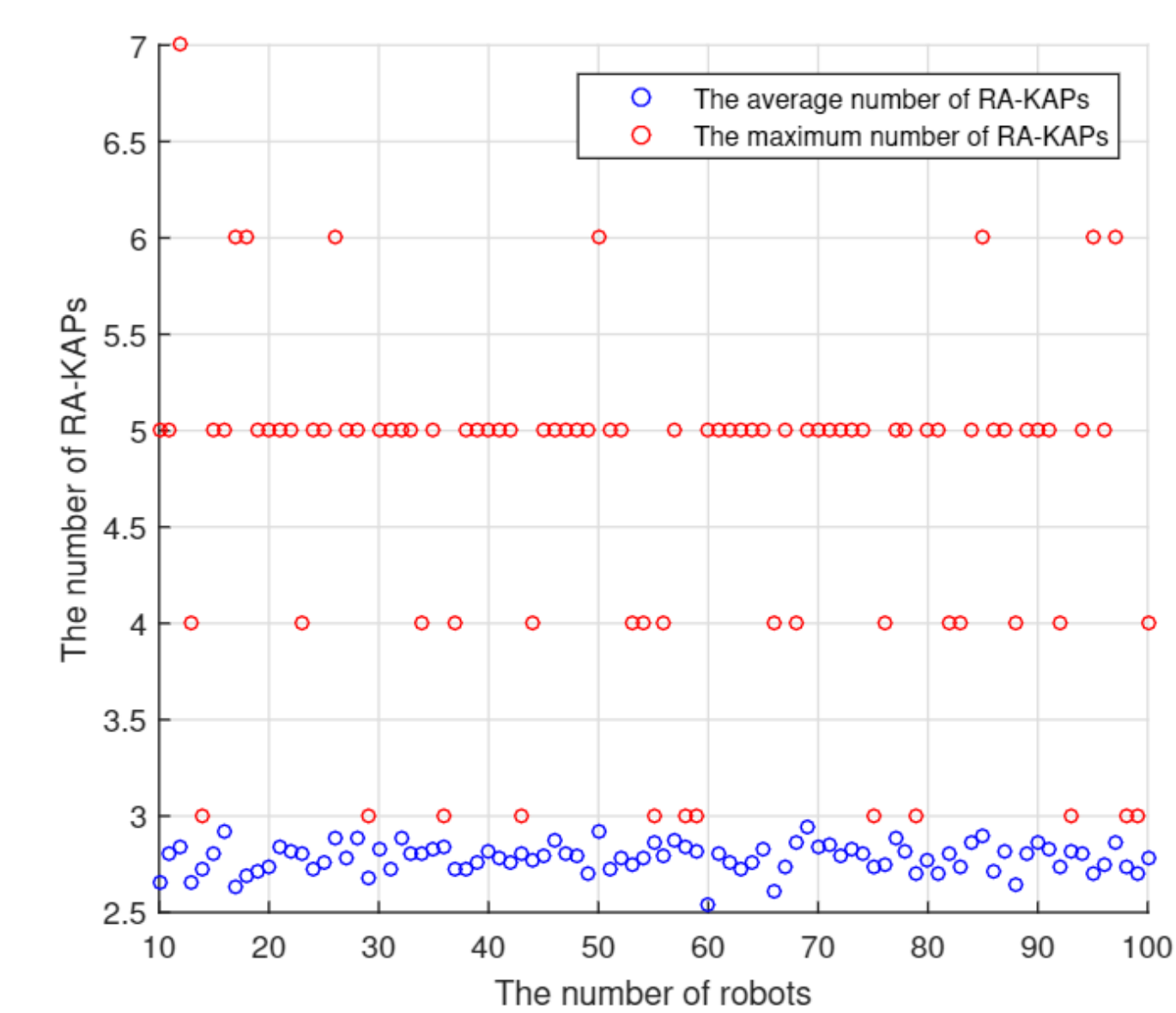


Fig. 3. For a given number of robots (varying from 10 to 100), the average and maximum number of RA-KAPs solved are less than 3 and 7 respectively. Results are based on 100 simulations with randomly generated mean and variance for travel distance of each robot.

Conclusion

- We present a novel approach that uses the solutions of a small number of deterministic RA-KAPs to solve a multi-robot team formation problem optimally.
- **We analyze the relationship between CC-KAP and RA-KAP on variance-mean plane. The geometric insight is helpful for solving other problems with chance constraint.**
- **We present simulation results showing that our method is efficient and scalable with the number of robots and the uncertainty in travel distance capacity.**

Acknowledgements

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