Explainable Multi-Robot Motion Planning via Segmentation

Justin Kottinger[1], Shaull Almagor[2], and Morteza Lahijanian[1]

I. Introduction

Multi-Robot Motion Planning (MRMP) is a fundamental problem in robotics and artificial intelligence (AI) where the goal is to calculate trajectories for multiple robots such that every vehicle safely reaches their respective goal when all trajectories are executed simultaneously. Applications include warehouse robots, search and rescue operations, planetary exploration, etc. There are many works that solve the MRMP problem in both the discrete (e.g., [1]–[3]) and continuous (e.g., [4]–[8]) domains. Yet, one limitation of those methods is their inability to *explain* their plans to human users [9]. This limitation hinders MRMP algorithms' use in safety-critical applications, such as air-traffic control, because a human cannot validate the plans. To this end, our study focuses on developing *explainable* MRMP algorithms that enable a human controller to efficiently validate automatically generated MRMP plans.

This paper presents our progress on explainable MRMP. We base explanations on the simplicity of visual human validation. Specifically, works [10] and [11] showed recognizing line intersections occurs very early in the cognitive process (namely in the primary visual cortex). Thus, MRMP can be explained using a collection of non-intersecting trajectory segments. Fig. 1 shows an example of such an explanation.

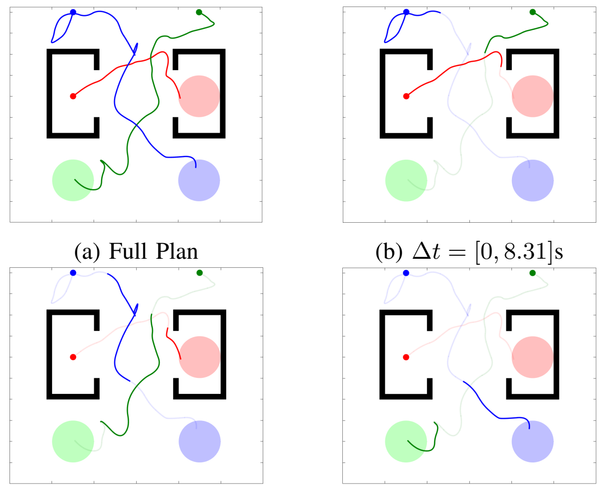
Work [12] studied such explanations in the discrete domain. They showed that as the number of disjoint-segments required to explain the plan decreases, the ease of explainability increases. They also proved that finding optimal explanations for existing plans takes polynomial time, whereas generating plans for explainability is, at best, NP-Complete.

II. Problem Statement

We are interested in realistic mobile robotic systems operating within a 2-dimensional continuous workspace with the goal of designing computationally-tractable MRMP algorithms that generate sound and easily explainable plans. We formally define our *Explainable MRMP* problem as follows: Given k kinodynamically constrained robots with unique start and goal regions, and a user-specified bound $r \in \mathbb{N}$ on the number of disjoint-segments, find a controller $\mathbf{u}_i : [0, t_f] \to U_i \in \mathbb{R}^{n_i}$ for every robot $i \in \{1, \dots, k\}$ such that the obtained plan T drives every robot safely to their respective goal within some finite time $t \leq t_f$ *and* T can be explained using $m \leq r$ disjoint-segments.

[1]Smead Aerospace Engineering Sciences, University of Colorado Boulder, firstname.lastname@colorado.edu

[2]The Henry and Marilyn Taub Faculty of Computer Science, Technion, Israel, shaull@technion.ac.il



(a) Full Plan (b) $\Delta t = [0, 8.31]$s (c) $\Delta t = [8.31, 17.1]$s (d) $\Delta t = [17.1, 22.4]$s

Fig. 1: A plan for three robots in (a) which is visually explained via disjoint-segments in (b)-(d). The small and large circles are the initial and goal regions, respectively.

This problem is challenging because the exponential growth of the state space and the kinodynamical constraints both complicate planning.

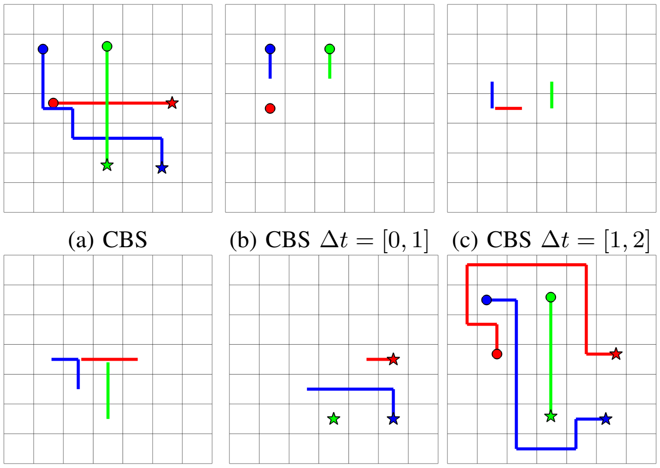
III. Approach

We present two algorithms to solve our Explainable MRMP problem. First, we present a centralized and continuous approach known as Multi-Agent Plan Segmenting X (MAPS-X), where X can be any centralized tree-based motion planner [13]. MAPS-X computes satisfactory motion plans based on a user defined explanation bound r but suffers from the exponential growth of the state space due to the centralized nature of X. To counter this, we present another recently proposed explainable planner known as Explanation-Guided Conflict-Based Search (XG-CBS) [14].

A. Centralized Explainable MRMP (MAPS-X):

Recall that centralized sampling-based tree planners work by combining each robot into a single meta-robot, and then growing a dynamically feasible tree in the composed state space through repeated sampling and propagation procedures. They output a plan T for the meta-robot and individual trajectories are extracted. Out-of-the-box sampling-based tree planners cannot solve the Explainable MRMP problem due to their inability to control the number of disjoint-segments.

MAPS-X [13] gives such planners the ability to explain their plans. As planner X grows the tree, every node is given a cost equivalent to the number of disjoint-segments



(a) CBS (b) CBS $\Delta t = [0, 1]$ (c) CBS $\Delta t = [1, 2]$

(d) CBS $\Delta t = [2, 4]$ (e) CBS $\Delta t = [4, 8]$ (f) XG-CBS, $r = 1$

Fig. 2: A shortest length plan from CBS in (a) and its explanation in (b)-(e) vs. an optimally explained plan from XG-CBS

required to explain the plan up to that node. The node is only added if it can satisfactorily be explained (i.e. $m \leq r$). The result is a plan T that solves the Explainable MRMP problem. Furthermore, the disjoint-segments are embedded in the solution so no additional computation is needed. We refer the reader to [13] for details.

B. *Decentralized Explainable MRMP (XG-CBS)*

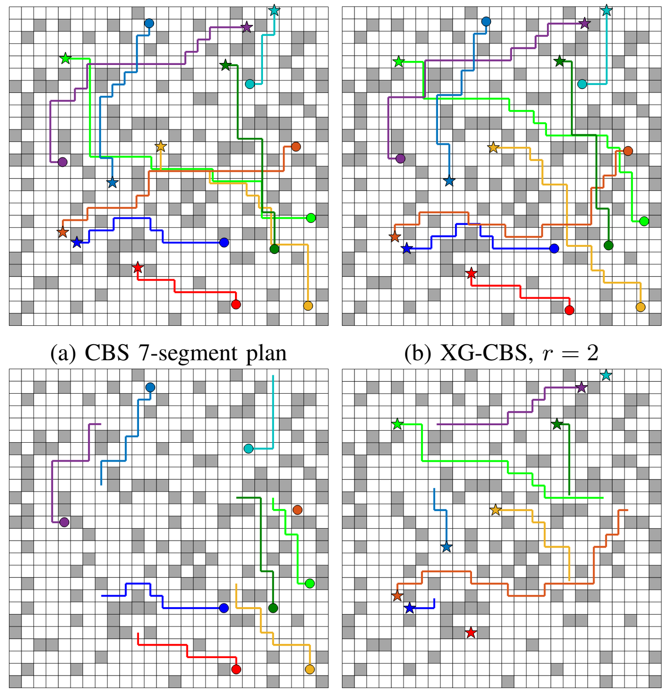
We now present a scalable explainable MRMP algorithm that avoids the exponential growth of the state space. We reduce the problem to a graph $G = (V, E)$ by abstracting the workspace into a finite set of discrete vertices V and assume control laws that guarantee the realization of edges E with a fixed time duration.

Work [12] found a plan T using a centralized A^*-based approach. We instead extend a well-known decentralized Multi-Agent Path Finding (MAPF) algorithm known as Conflict-Based Search (CBS) [3] to plan with explanations. CBS individually plans for each robot using graph search (e.g. A^*). It then checks the plans for conflicts (e.g. collisions). If conflicts occur, CBS resolves them by adding constraints in the form of time-dependent obstacles and re-calculates paths that respect the constraints. The process repeats until a solution is found or the search is exhausted.

We modified CBS to obtain a new algorithm dubbed Explanation-Guided CBS (XG-CBS) [14]. This involved introducing *segmentation conflicts*, which occur when a proposed plan cannot be satisfactorily explained (i.e. $m > r$). These conflicts are resolved by placing appropriate constraints and replanning with an explanation-guided A^* graph search algorithm. We refer the reader to [14] for details.

IV. Case Studies

We begin with a case study in the continuous domain using MAPS-X (see [13] for more examples). We use MAPS-X with rapidly-exploring random tree (RRT) [15] as planner X. We consider three robots with second-order linear dynamics operating in the environment shown in Fig. 1. MAPS-RRT found a solution that can be explained in 3 images in approximately 30 seconds (Figs. 1b-1d).



(a) CBS 7-segment plan (b) XG-CBS, $r = 2$

(c) XG-CBS, $\Delta t = [0, 6]$ (d) XG-CBS, $\Delta t = [6, 38]$

Fig. 3: Example of XG-CBS simplifying an explanation.

We now present results in the discrete domain using XG-CBS (see [14] for more examples). We begin with the problem shown in Fig. 2a where a user may notice a possible collision between the red and green robots at $t = 2$. However, the explanation depicted in Figs. 2b-2e clearly shows the red robot waiting for the green to pass before proceeding, thus avoiding collision. XG-CBS produced an improved explanation, shown in Fig. 2f, after 0.5 seconds of computation by setting $r = 1$.

XG-CBS continues to produce shorter explanations than traditional CBS as the number of robots increases. For example, the problem shown in Fig. 3 contains 9 robots in a large warehouse environment. CBS found a solution (Fig. 3a) that requires seven segments to explain while the solution from XG-CBS (Fig. 3b) only requires two segments to explain (Figs. 3c-3d). Our results show that, in general, there is an inverse relationship between shortest-path plans and shortest-explanation plans.

V. Conclusion

This work leverages the humans' cognitive process to explain MRMP plans using disjoint-segments within a 2-dimensional workspace. The MAPS-X [13] framework is capable of solving our Explainable MRMP problem in continuous space and time using centralized algorithms. Alternatively, XG-CBS [14] can scale to many more robots by leveraging an abstraction-based decentralized algorithm. Future work will propose a decentralized and continuous algorithm for solving our Explainable MRMP problem.

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