Search Algorithms for Multi-Agent Teamwise Cooperative Path Finding [Extended Abstract]

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Introduction

Multi-Agent Path Finding (MA-PF) seeks to fnd collisionfree paths for multiple agents from their respective start locations to their respective goal locations. This paper investigates a generalization of MA-PF called Multi-Agent Teamwise Cooperative Path Finding (MA-TC-PF) (Fig. 1), which differs from MA-PF (Stern et al. 2019) by introducing the notion of teams: Each agent belongs to at least one team, and teams are not required to be mutually disjoint to each other. Each team has its own objective to be minimized such as flowtime (i.e., min-sum) or makespan (i.e., min-max), and MA-TC-PF seeks to minimize an objective vector, where each component of the vector corresponds to the objective of a team. In general, there is more than one team, and MA-TC-PF is thus a multi-objective planning problem. The goal of MA-TC-PF is to fnd a maximal set of cost-unique Paretooptimal solutions, whose corresponding objective vectors form the Pareto-optimal front. A solution is Pareto-optimal if one cannot improve over one objective without deteriorating another objective. When there is only one team that includes all agents, MA-TC-PF becomes MA-PF. MA-TC-PF also differs from the existing Multi-Agent Multi-Objective Path Finding (MA-MO-PF) (Ren, Rathinam, and Choset 2022) since an action of each agent incurs a scalar cost as opposed to a vector cost in MA-MO-PF. To solve MA-TC-PF, we modify CBS (Sharon et al. 2015) and M* (Wagner and Choset 2015) and name the new algorithms TC-CBS and TC-M* respectively. TC-CBS is incomplete (elaborated later) for certain cases of MA-TC-PF, while TC-M* is complete for all possible cases. Both algorithms are guaranteed to fnd the entire Pareto-optimal front for the cases where they are complete. For the rest of the paper, we assume the reader is familiar with CBS (Sharon et al. 2015) and M* (Wagner and Choset 2015), and we focus on TC-CBS. More details can be found in (Ren et al. 2023).¹

Figure 1: An example of MA-TC-PF with two teams, where team 1 includes the yellow (Y) and blue (B) agents while team 2 includes the blue (B) and red (R) agents. Team 1 aims to minimize the maximum arrival times of both agents, while team 2 aims to minimize the sum of arrival times.

Method

TC-CBS Algorithm: The proposed Teamwise Cooperative Confict-Based Search (TC-CBS) algorithm follows a similar workflow as CBS. The main differences are: First, given a (high-level) node P_k (hereafter referred to as "node") and its corresponding joint path π_k (a set of individual paths of each agent), TC-CBS computes an objective vector $\vec{g}(\pi_k)$ based on the teams, instead of computing a scalar cost value g as in CBS. Consequently, nodes in OPEN are prioritized in the lexicographic (abbreviated as lex.) order based on their cost vectors, and in each iteration, a lex. min node is popped from OPEN for processing. Second, since there are multiple Pareto-optimal solutions in general, TC-CBS stores the cost vector of all the Pareto-optimal solutions found during the search in a set C . Each vector in C identifies a unique node and thus a cost-unique solution. Third, to fnd all costunique Pareto-optimal solutions, TC-CBS terminates when OPEN depletes, while CBS terminates when the frst solution is found. Additionally, whenever a node P_k is popped from OPEN or newly generated, P_k is tested for filtering, i.e., P_k is discarded if the objective vector in P_k is dominated (Ren, Rathinam, and Choset 2022) by or equal to any existing objective vectors in C.

Discussion and Properties of TC-CBS: A problem instance is feasible if there exists a solution. Given a feasible instance, TC-CBS is *complete* if it terminates in fnite time. A MA-TC-PF problem is called *fully cooperative* if every team contains all the agents. For fully cooperative MA-TC-PF, TC-CBS is guaranteed to be complete, and is guaranteed to fnd all cost-unique Pareto-optimal so-

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Figure 2: An example where TC-CBS is incomplete. The grey area shows the vectors dominated by the green solution.

Figure 3: Numerical results of TC-CBS and TC-M* for fully cooperative MA-TC-PF problems with min-sum and minmax as the two objectives. The horizontal axis shows the number of agents (N) , the left vertical axis shows the success rates (Succ. Rates) while the right axis shows the number of conficts resolved (#Conficts). Two maps are: 16x16 Empty and 32x32 Random.

lutions. For MA-TC-PF that is not fully cooperative (i.e., there exists a team that does not contain all the agents), TC-CBS is incomplete: TC-CBS fails to terminate in fnite time even if the problem instance is feasible. In short, the condition for TC-CBS being complete is: there is a fnite number of joint paths whose objective vectors are non-dominated by the Pareto-optimal front (similar to Lemma 4 in (Ren, Rathinam, and Choset 2022)). This condition may not hold for MA-TC-PF that is not fully cooperative. An example is shown in Fig. 2: there are two agents $I = \{i, j\}$ and two teams $T_1 = \{i\}, T_2 = \{j\}$; the objective vector is $(g^{T_1}, g^{T_2}) = (g^i, g^j)$. Consider the case where a conflict $(i = 1, j = 2, v, t)$ is detected, and is split into constraints (i, v, t) and (j, v, t) , which results in two new nodes (red and green). For either of the two nodes, one agent's path cost may increase (as a constraint is added), while the other agent's path cost remains the same. Consider the case where the green node leads to the only Pareto-optimal solution, and the red node still contains conficts. As a result, there can be an infnite number of joint paths whose objective vectors are non-dominated by the Pareto-optimal front, and TC-CBS never terminates since OPEN never depletes.

Experimental Results

MA-PF with Both Min-sum and Min-max Objectives We start with fully cooperative MA-TC-PF problems with two teams and each team includes all agents. One team has the min-sum objective while the other team has the min-max objective. As shown in Fig. 3, TC-CBS achieves higher success rates than TC-M*, and is tested with up to 20 agents. Although TC-CBS is incomplete for general MA-TC-PF

Figure 4: Each agent (circle) needs to move to its goal (star), and the aim is to fnd all trade-offs between agents. In this example, Solution 7 (highlighted in blue in the table) has the minimum sum of individual arrival times.

problems, it runs faster than TC-M* in general. We report the corresponding statistics of the number of Pareto-optimal solutions over succeeded instances here: for both Empty 16x16 and Random 32x32 maps and all Ns that are tested, the minimum and median number of solutions is one, and the maximum number of solutions is up to three. It indicates that, in these instances, the min-sum and min-max objectives can often be optimized at the same time.

Example: Explanation for MA-PF Solutions MA-TC-PF has the potential to answer explanatory questions about MA-PF solutions. As shown in Fig 4, there are four agents and each agent is itself a team. Each team (i.e., agent) aims to minimize its own arrival time. The table in Fig 4 shows all cost-unique Pareto-optimal solutions which indicate possible trade-offs between the teams. Consider a possible question raised by the user of MA-PF planners: among all confict-free solutions, can agent 1's arrival time be reduced without worsening the min-sum objective of all agents? The table provides the answer to the question, which is NO in this example. Answering explanatory questions may increase trust of users and transparency of intelligent systems.

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