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k -Color Multi-Robot Motion Planning

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by

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Abstract

We present a simple and natural extension of the *multi-robot motion planning* problem where the robots are partitioned into groups (colors), such that in each group the robots are interchangeable. Every robot is no longer required to move to a specific target, but rather to some target placement that is assigned to its group. We call this problem *k-color multi-robot motion planning* and provide a sampling-based algorithm specifically designed for solving it. At the heart of the algorithm is a novel technique where the *k-color* problem is reduced to several discrete multi-robot motion planning problems. These reductions amplify basic samples into massive collections of free placements and paths for the robots. We demonstrate the performance of the algorithm by an implementation for the case of disc robots moving among polygonal obstacles in the plane and show that it successfully and efficiently copes with a variety of challenging scenarios, involving many robots, while a simplified version of this algorithm, that can be viewed as an extension of a prevalent sampling-based algorithm for the *k-color* case, fails even on simple scenarios. Interestingly, our algorithm outperforms a state-of-the-art implementation for the standard multi-robot problem, in which each robot has a distinct color.

This work was presented in the *Workshop on the Algorithmic Foundations of Robotics* and has been invited to a special issue of the *International Journal of Robotics Research* that is dedicated to selected papers from this conference.

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1

Introduction

Motion planning is a fundamental problem in robotics and has applications in different fields such as the study of protein folding, computer graphics, computer-aided design and manufacturing (CAD/CAM), and computer games.

The problem of motion planning, in its most basic form, is to find a collision-free path for a robot from start to goal placements while moving in an environment cluttered with obstacles.

An obvious extension of this problem is *multi-robot motion planning*, where several robots share a workspace and have to avoid collision with obstacles as well as with fellow robots. In many situations it is natural to assume that some robots are identical, in form and in functionality, and therefore are indistinguishable. In this setting every target position should be occupied by some robot of a kind (and not necessarily by a specific robot).

We consider the problem of *k-color multi-robot motion planning*—a simple and natural extension of the multi-robot problem where the robots are partitioned into k groups (colors) such that within each group the robots are interchangeable. Every such group has a set of target positions, of size equal to the number of robots in that group. Every robot is no longer required to move to a specific target, but rather to some target position that is assigned to its group. However, we still require that all

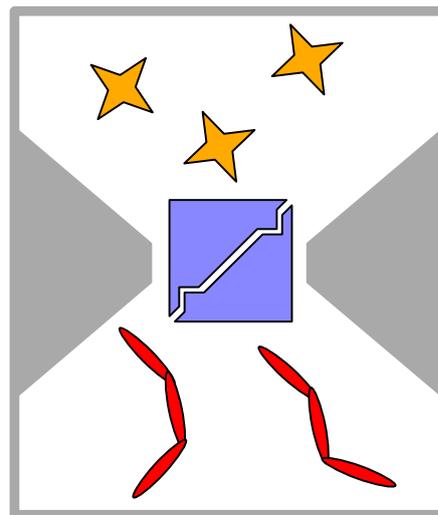


Figure 1.1: An example of a 3-color scenario with three different groups of robots. The star-shaped (orange) robots are required to exchange “rooms” with the snake (red) robots while the two puzzle-like (purple) robots should return to their start positions in the end of the motion. Obstacles are drawn in gray.

the target positions will be covered by the end of the motion of the robots. We term the special case where $k = 1$ the *unlabeled multi-robot motion planning* problem.

As an example consider a fleet of mobile robots operating in a factory that are given the task of cleaning a set of specific locations. The robots are indistinguishable from one another, and therefore any robot can be assigned to any location. Now assume that in addition to the mobile robots, another class of maintenance robots is employed by the factory; again, we consider all the maintenance robots to be of the same kind and interchangeable for the given task. This turns the unlabeled problem into a k -color problem, where $k = 2$ in this case.

From now on we will refer to the classic multi-robot motion planning problem as *fully-colored*, as it is a special case of the k -color problem where k is equal to the number of robots and every group is of size one.

1.1 Previous Work

Throughout this thesis we will assume some familiarity with the basic terms in the area of motion planning. For more background on motion planning, see, e.g., [5, 18].

The first efforts in motion planning in general, and the multi-robot case in particular, were aimed toward the design of *complete* algorithms, guaranteed to find a solution when one exists or report that none exists otherwise. Schwartz and Sharir were the first to give [25] a complete algorithm for a multi-robot problem, specifically dealing with the case of coordinating disc robots in the plane. The running time of their algorithm is exponential in the number of robots. A work by Hopcroft et al. [11] presented soon after suggested that in some cases the exponential running time may be unavoidable, showing that even the relatively simple setting of rectangular robots bound in a rectangular region is PSPACE-hard in the number of robots.

The hardness of the multi-robot problem involving a large number of robots can be attributed to its high number of *degrees of freedom* (or *dofs*)—the sum of the dofs of the individual robots. Some efforts were made in the direction of reducing the effective number of dofs. Aronov et al. [2] showed that for systems of two or three robots a path can be constructed, if one exists, where the robots move while maintaining contact, thus reducing the number of dofs by one or two, depending on the number of robots. van den Berg et al. [27] proposed a general scheme for decomposing a multi-robot problem into a sequence of subproblems, each consisting of a subset of robots, where every subproblem can be solved separately and the results can be combined into a solution for the original problem. This method reduces the number of dofs that need to be treated simultaneously from the number of dofs of the entire problem to the number of dofs of the largest subproblem.

An opposite approach to the complete planners is the *decoupled* approach, trading completeness with efficiency. Decoupled algorithms solve separate subproblems (usually for individual robots) and combine the individual solutions into a global solution. Although this approach can be efficient in some cases, it does not guarantee finding a solution if one exists and usually works only for a restricted set of problems. An example of such an algorithm can be found in the work of van den Berg and Overmars [28] where every robot is given a

priority and for each robot, the motion path is constructed to avoid collision with both static obstacles and lower-priority robots that are considered as moving obstacles. In other works, as in Leroy et al. [19], individual paths are computed and velocity tuning is performed to avoid collision between robots.

In recent years, the *sampling-based* approach to solving motion-planning problems has become increasingly popular due to its efficiency, simplicity and the fact that it is applicable to a wide range of problems. Unlike the complete planners that explicitly build the *configuration space* of a given problem, i.e., the state of all possible configurations of a robot, sampling-based algorithms construct an implicit representation of a robot configuration space by sampling this space for valid robot placements and connecting near-by samples. The connections between samples form a *roadmap* whose vertices describe valid placements for the robot and the edges represent valid paths from one placement to the other. Due to the implicit representation of the configuration space and their simplicity, sampling-based algorithms tend to be much faster than complete planners in practice, and are applicable to problems with a large number of dofs such as the multi-robot problem. Although these algorithms are not complete, many of them are *probabilistically complete*, that is, they are guaranteed to find a solution, if one exists, given sufficient amount of time. Examples of such algorithms are the PRM algorithm [13] by Kavraki et al. and the RRT algorithm [17] by Kuffner and LaValle. Such algorithms can be easily extended to the multi-robot case by considering the fleet of robots as one large composite robot [24]. Several tailor-made sampling-based algorithms have been proposed for the multi-robot case [10, 29]. For more information on sampling-based algorithms see, e.g., [18].

An abstract form of the multi-robot motion planning problem is the *pebble motion on graphs problem* [16]. This is a general case of the famous *15-puzzle* [20] where pebbles occupying distinct vertices of a given graph are moved from one set of vertices to another, where the pebbles are bound to move on the edges of the graph. This field of research was extensively studied in the last three decades, and an in-depth overview is given in Chapter 3. Even though there is a fundamental difference between the pebble problem and the multi-robot problem—the former is held in a discrete domain while the latter in the continuous—still the two problems are interweaved and exhibit several points of similarity. Kornhauser et al. were the first [16] to suggest that an algorithm for the pebble may be found useful in tackling the multi-robot motion planning problem, contemplating “... it is hoped that the techniques introduced for the solution of the pebble coordination problem may be applicable to special cases of the general geometric problem”.

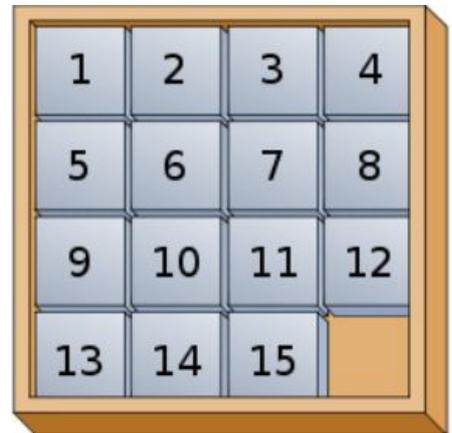


Figure 1.2: The famous 15-puzzle. Figure was taken from en.wikipedia.org/wiki/15_puzzle.

1.2 Contribution

We present a sampling-based algorithm for the k -color problem (for any k). This algorithm is aimed to solve the most general cases of this problem and does not make any assumptions regarding the workspace or the structure of the robots.

Our algorithm for the k -color problem—the KPUMP algorithm—reduces the k -color problem to several discrete pebble problems. Specifically, a sample generated by KPUMP represents a local k -color problem that is embedded in a variant of the pebble motion problem. Those pebble problems are constructed in a manner that enables the algorithm to transform movements of pebbles into valid motions of the robots. This allows KPUMP to generate a wide range of motions and placements for the robots with minimal investigation of the configuration space, thus reducing the dependence of the algorithm on costly geometric tools such as the collision detector.

As reflected in the experiments reported below for the case of disc robots in the plane, KPUMP proves to be efficient, even on challenging scenes, and is able to solve problems involving a large number of robots using a modest number of samples. Interestingly, it performs well even on inputs of the standard (fully-colored) multi-robot problem.

This algorithm is simple to implement and does not require special geometric components beyond single-robot local planners and single-robot collision detectors. We compare the performance of our algorithm with a simplified version of KPUMP that can be considered as a variant of the PRM algorithm for the same problem. We note that the latter performs much slower than KPUMP and fails to solve even problems that are considered to be simple for KPUMP. Moreover, concentrating on the fully-colored case, KPUMP outperforms a state-of-the-art implementation of the PRM algorithm. We show that by making a simple assumption on the work of the connection generator, it can be proved that KPUMP is probabilistically complete.

Our discussion will mainly focus on UPUMP—an algorithm for the unlabeled case, since its extension for the k -color case, namely KPUMP, is almost straightforward. The experiments though will demonstrate the power of KPUMP for various values of k .

The organization of the paper is as follows. In Chapter 2 we give formal definitions of the unlabeled and k -color problems. In Chapter 3 we present a variant of the pebble problem and discuss its properties which will be exploited by our algorithms. In Chapter 4 we present UPUMP. In Chapter 5 we describe the changes to UPUMP that are necessary in order to transform it into KPUMP. In Chapter 6 the completeness of our algorithms is discussed. We present experimental results for the case of disc robots moving among polygonal obstacles in the plane in Chapter 7 and discuss certain properties of our techniques in Chapter 8, as well as further work.

2

Preliminaries and Terminology

Let r be a robot operating in the workspace W . We denote by $\mathcal{F}(r)$ the *free space* of a robot r —the collection of all collision-free *single-robot configurations*.¹ Given $s, t \in \mathcal{F}(r)$, a *path* for r from s to t is a continuous function $\pi : [0, 1] \rightarrow \mathcal{F}(r)$, such that $\pi(0) = s, \pi(1) = t$.

Unlabeled Multi-Robot Motion Planning. We say that two robots r, r' are *geometrically identical* if $\mathcal{F}(r) = \mathcal{F}(r')$ for the same workspace W . Let $R = \{r_1, \dots, r_m\}$ be a set of m geometrically identical robots, operating in a workspace W . We may use \mathcal{F} to denote $\mathcal{F}(r_i)$ for any $1 \leq i \leq m$. Let $C = \{c_1, \dots, c_m \mid c_i \in \mathcal{F}\}$ be a set of m single-robot configurations. C is a *configuration* if for every $c, c' \in C$, with $c \neq c'$, the robots $r, r' \in R$, placed in c, c' , do not collide. Notice that we reserve the unqualified term *configuration* to refer to a set of m collision-free single-robot configurations. Other types of configurations will be qualified: single-robot configurations and pumped configurations.

Given two configurations $S = \{s_1, \dots, s_m\}, T = \{t_1, \dots, t_m\}$, named *start* and *target*, respectively, we define $\mathcal{U} = (R, S, T)$ as the *unlabeled problem*, which is shorthand for the *unlabeled multi-robot motion planning problem*. Our goal is to find an *unlabeled path* $\pi_{\mathcal{U}}$, defined as follows. Firstly, $\pi_{\mathcal{U}}$ is a collection of m paths $\{\pi_1, \dots, \pi_m\}$ such that for every i , π_i is a collision-free path for the robot r_i from s_i to *some* $t \in T$. Secondly, the robots have to remain collision-free while moving on the respective paths, i.e., for every $\theta \in [0, 1]$, $\pi_{\mathcal{U}}(\theta) = \{\pi_1(\theta), \dots, \pi_m(\theta)\}$ is a configuration. Notice that this also implies that $\pi_{\mathcal{U}}(1)$ is some permutation of T .

Throughout this thesis, we use the notation $r(c) \subset \mathcal{C}$, for $c \in \mathcal{F}$, to represent the portion of the configuration space covered by a robot $r \in R$ placed in the single-robot configuration c . Note that two robots from R collide, when placed in $c, c' \in \mathcal{F}$, if $r(c) \cap r(c') \neq \emptyset$.

¹We assume that $\mathcal{F}(r)$ is an open set. This is not critical in the algorithms below as we assume that the robot never moves in contact with the obstacles.

k -Color Multi-Robot Motion Planning. The k -color problem \mathcal{L} is defined by the set of unlabeled problems $\{\mathcal{U}_1, \dots, \mathcal{U}_k\}$, where $\mathcal{U}_i = (R_i, S_i, T_i)$ and $|R_i| = m_i$. Now we wish to find for every \mathcal{U}_i an unlabeled path $\pi_{\mathcal{U}_i}$ with the additional requirement that robots from different unlabeled problems do not collide. A special case of this problem, usually named simply *multi-robot motion planning*, is a k -color problem where for every \mathcal{U}_i it holds that $|R_i| = 1$. In our context we call this special case *fully-colored*.

3

The Pebble Motion Problem

In this chapter we survey several results that are related to the *pebble motion on graph* problem. Then, in preparation for the algorithm presented in the next chapter, we discuss a variant of the problem that can be viewed as a discretization of the unlabeled problem. This discretization is defined in a manner that will allow us to transform local unlabeled problems into pebble problems such that a movement of the pebbles can be transformed back into valid robot motions. We explain below where our formulation is different from the standard presentation of the pebble motion problem.

3.1 Overview

The pebble-motion-on-graph problem is a general case of the famous *15-puzzle* [20] where pebbles occupying distinct vertices of a given graph are moved from one set of vertices to another. Formally, given a graph and a set of distinct pebbles—each pebble is assigned with a start and target a vertex—the goal is to move the pebbles from start to target, restricting each vertex to accommodate at most one pebble at a time. This problem was extensively studied in the past three decades and various results exist.

The first group of results focuses on the question of feasibility of a given pebble problem—does a solution exists to the given instance of the problem? Wilson [32] considered the case of a bi-connected graph¹ with a single unoccupied vertex and described a feasibility criterion. Kornhauser et al. [16, 15] extended the result of Wilson to general graphs and an arbitrary number of pebbles. The extended feasibility criterion can be validated in polynomial time. Another interesting result described in this work is the bound on the number of pebble moves that is necessary and sufficient for solving a given instance. Specifically, it is shown that

¹A graph is bi-connected if it is connected and remains connected after a removal of any single vertex.

every pebble problem can be solved using $O(n^3)$ moves, and that some problems require $\Omega(n^3)$ moves—making the bound tight (where n is the number of vertices in the graph, and consequently, the maximal number of pebbles). More recently, Auletta et al. [3] described a linear-time feasibility algorithm for the case of a tree. Goraly and Hassin [9] extended this result and provide a linear-time feasibility algorithm for the general graph case. Moreover, their algorithm applies to a generalized version of the pebble problem, that allows the target positions to be shared among some of the pebbles, similarly to the k -color problem.

We proceed to describe techniques for finding a concrete solution. Kornhauser et al. mention that an algorithm can be deduced from their feasibility criterion, although it may require some effort, as a concrete description of the algorithm is not provided. An algorithm by Luna and Bekris [21] demonstrates that the pebble problem can be solved using two relatively simple primitives—one that pushes a group of pebbles on a path, and the other that swaps the positions of two pebbles. A recent work by Yu and LaValle [33] demonstrates that the unlabeled variant of the pebble problem can be efficiently solved using flow algorithms. We also mention the M^* algorithm by Wanger et al. [30], that can be applied to the pebble problem, although it is suitable for a wider range of problems and can be used for solving the continuous multi-robot motion planning problem [31].

The problem of finding an optimal solution to the pebble problem, i.e., one that minimizes the number of moves, is known to be NP-hard, even for the generalized 15-puzzle on an $n \times n$ grid [8]. In [4] the complexity of other variations of the pebble problem is discussed, as well as several approximation algorithms. We mention that finding an optimal solution to a simplified version of the pebble problem with a single pebble and movable pebble-obstacles is NP-hard as well [22].

3.2 Formal Definition

We now formally describe the variant of the pebble problem that will be used throughout this thesis. A pebble problem [16] $\mathcal{P}(G, S, T, m)$ is defined by an undirected graph $G = (V, E)$, and two sets of vertices $S, T \subseteq V$, where $|S| = |T| = m$. A *pebble placement* is an ordered set of m distinct vertices of V . Initially, m identical pebbles τ_1, \dots, τ_m are placed in S . We wish to find a chain of placements $\pi^* = P_1, \dots, P_\ell$, called a *pebble path*, which obeys the following set of rules. Firstly, we demand that $P_1 = S$. Secondly, for every two consecutive placements $P = \{p_1, \dots, p_m\}, P' = \{p'_1, \dots, p'_m\}$ and every $1 \leq i \leq m$ it holds that $(p_i, p'_i) \in E$ or $p_i = p'_i$, i.e., the pebble τ_i is allowed to stay in its current vertex or move to a neighboring vertex in the graph.

Next we depart from the problem definition in [16]. We demand that P_ℓ is some permutation of the elements of T (The original formulation [16] specified which pebble will reside on which specific vertex of T). We do, however, impose an additional requirement—the *separation rule*—which requires that the pebbles will move separately, i.e., for every two consecutive placements P, P' , as defined above, exactly one pebble τ_i makes a move on an edge, while the other pebbles remain stationary. More formally, there exists $1 \leq i \leq m$ such that $(p_i, p'_i) \in E$ and for every $j \neq i$ it holds that $p_j = p'_j$. The reason for this restriction will become clear later on.

3.3 Solvability

We provide a simple test to identify whether a given pebble problem has a solution. We start with a pair of basic definitions.

Definition 1. Let V' be a pebble placement of $\mathcal{P}(G, S, T, m)$ and let $\{G_1, \dots, G_h\}$ be the set of maximal connected subgraphs of G , where $G_i = (V_i, E_i)$. The *signature* of V' is defined as $\text{sig}(G, V') = \{|V' \cap V_i|\}_{i=1}^h$.

Namely, the signature of a placement is the number of pebbles in every connected component. Using this definition we define an equivalence relation between placements.

Definition 2. Let V', V'' be two placements of $\mathcal{P}(G, S, T, m)$. We say that the two placements are equivalent if $\text{sig}(G, V') = \text{sig}(G, V'')$ and denote this property by $V' \equiv V''$.

We emphasize that this equivalence relation is only defined between placements of the same graph. The variant of the pebble problem used in this work possesses the following property, which states that there exists a pebble path between every two equivalent pebble placements. This property plays a central role in the design of the UPUMP algorithm, presented in the next chapters.

Lemma 1. *For every pebble problem $\mathcal{P}(G, S, T, m)$ such that $S \equiv T$, there exists a pebble path from S to T .*

Proof. This lemma is a generalization of [15, Section 3, first Lemma] where an algorithm for the case of a connected graph is given. We mention that this algorithm constructs a spanning tree of G and restricts the movements of the pebbles to the edges of the tree. \square

From now on, we will refer to the algorithm that solves the pebble problem as *pebble solver*, which given a pebble problem returns a pebble path, if one exists.

4

Algorithm for the Unlabeled Case: Pumped Configurations

In this chapter we present our main contribution — a sampling-based algorithm for the unlabeled problem. The algorithm, UPUMP, generates a collection of geometrically-embedded graphs. These are called *pebble graphs* and enable to map valid movements of pebbles from one pebble placement to the other on these graphs, into motions of robots between configurations in the continuous space. The vertices of such pebble graphs are single-robot configurations while the edges represent single-robot paths. We generate a pebble graph by sampling a set of single-robot configurations, called *pumped configurations*, of size larger than the actual number of robots, to seemingly accommodate an increased number of robots.

This technique makes use of the fact that our problem does not involve one complex robot, but rather a collection of robots operating in the same configuration space. This is in contrast with a popular sampling-based technique, which considers the group of robots as one *composite robot*. In our opinion, the latter suffers from an acute disadvantage compared to our technique. We will demonstrate this claim experimentally and discuss the benefits of UPUMP and KPUMP in depth later on, in Chapter 8.

After discussing the construction of pebble graphs and exploring their various properties we show that they can be connected to generate more complex paths where the robots not only move within a single pebble graph but also between different pebble graphs on collision-free paths. We conclude this chapter with a description of the sampling-based algorithm.

4.1 Construction of Pebble Graphs

We now define more formally some of the aforementioned structures. Recall that a configuration is a collection of m single-robot configurations, where m is the actual number of

robots, i.e., $|R|=m$, for which the m robots are collision-free.

Definition 3. Let $V = \{v_1, \dots, v_n\}$ for $n \geq m$ be a set of single-robot configurations such that for every $v \in V$ it holds that $v \in \mathcal{F}$, where $\mathcal{F} = \mathcal{F}(r)$ for some $r \in R$. V is a *pumped configuration* if every $C \subseteq V$, such that $|C|=m$, is a configuration.

This implies that a pumped configuration can accommodate an increased number of robots, n to be exact. A possible implementation of a procedure that generates a pumped configuration is given in Algorithm 1.

Given a pumped configuration V we construct the graph $G = (V, E)$ where the edges represent paths in \mathcal{F} for individual robots. We call it a *pebble graph*, and view it as embedded in the free configuration space. To generate the edges of G , and the respective paths, we utilize the *edge planner* mechanism that is described below. This, in turn, relies on the *local planner* component, which traditionally attempts to connect two single-robot configurations with a straight-line path, although a more sophisticated technique can be used.

Given $v, v' \in V$ such that V is a pumped configuration and $v \neq v'$, let π be a path for $r \in R$ from v to v' that was generated by the local planner. If for every $u \in V$, where $u \neq v, v'$, the robot r , while moving on π , does not collide with a (geometrically identical) robot placed in u , then the *edge planner* returns π . Otherwise, it reports failure.

A procedure for the creation of a pebble graph is described in Algorithm 2. The edge planner is applied on every pair $v \neq v'$ in V . Upon successful generation of a path $\pi_{v,v'}$ the edge (v, v') is added to G . An example of a pumped configuration, as well as its underlying graph, are given in Figure 4.1.

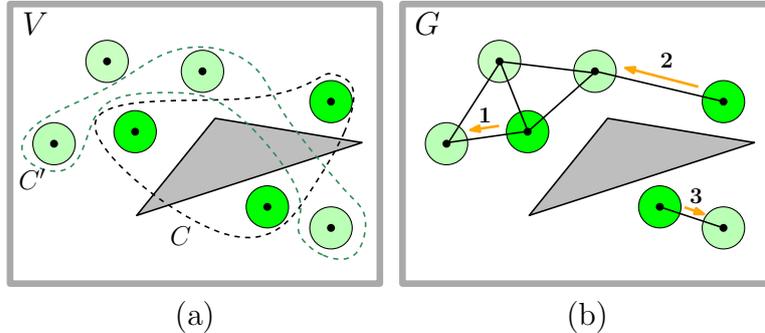


Figure 4.1: (a) Pumped configuration V with $m = 3, n = 7$, for the problem of disc robots in the plane. C, C' are two configurations such that $C, C' \subset V$. (b) The pebble graph G is induced by V using an edge planner that tries to connect pairs of single-robot configurations with a straight-line path. In addition, a path induced by a pebble path, from C to C' , is described, where the arrows describe the movements of the robots from one single-robot configuration to its neighbor, and the numbers indicate the order in which those movements occur.

Algorithm 1 PUMPED_CONFIGURATION(n)

```
1:  $V \leftarrow \emptyset$ 
2: while  $|V| \neq n$  do
3:    $v \leftarrow \text{RANDOM\_SAMPLE}()$ 
4:    $\text{valid} \leftarrow \text{TRUE}$ 
5:   for all  $v' \in V, v \neq v'$  do
6:     if  $r(v) \cap r(v') \neq \emptyset$  then
7:        $\text{valid} \leftarrow \text{FALSE}$ 
8:   if  $\text{valid}$  then
9:      $V \leftarrow V \cup \{v\}$ 
10: return  $V$ 
```

Algorithm 2 PEBBLE_GRAPH(n)

```
1:  $V \leftarrow \text{PUMPED\_CONFIGURATION}(n)$ 
2:  $E \leftarrow \emptyset$ 
3: for all  $v, v' \in V, v \neq v'$  do
4:    $\pi_{v,v'} \leftarrow \text{EDGE\_PLANNER}(V, v, v')$ 
5:   if  $\pi_{v,v'} \neq \perp$  then
6:      $E \leftarrow E \cup \{(v, v')\}$ 
7: return  $G = (V, E)$ 
```

4.2 Properties of Pebble Graphs

We now discuss the various properties of this special graph. We first note that every configuration $C \subset V$ is also a pebble placement for some pebble problem that is defined on G . A less obvious property of the pebble graph G , which is described in the following proposition, allows us to transform pebble paths into robot paths.

Proposition 1. *Let $G = (V, E)$ be a pebble graph and let $C, C' \subset V$ be two configurations such that $C \equiv C'$. Then there exists a path $\pi_{\mathcal{U}'}$ for $\mathcal{U}' = (C, C')$.*

Proof. By Lemma 1 there is a pebble path π^* for the pebble problem $\mathcal{P}(G, C, C', m)$. We transform the movements of the pebbles into π^* to a valid motion of the robots in the following manner. A movement of the pebble τ_i on the edge $(v, v') \in E$ is transformed to the motion of the robot r_i along the path $\pi_{v,v'}$. Notice that a collision between a robot and an obstacle cannot occur since the path was generated by the edge planner. Additionally, a moving robot cannot collide with another “stationary” robot that resides in some other vertex $u \in V$. Finally, a collision between two moving robots cannot occur since the pebble path π^* must respect the separation rule (Chapter 3), which states that at most one pebble is allowed to move at a given time. \square

4.3 Connecting Pebble Graphs

Proposition 1 implies that certain unlabeled problems can be solved using a single pebble graph. However, this statement does not hold for many other instances of the unlabeled problem. As an example, consider an unlabeled problem $\mathcal{U} = (S, T)$ in which there exists at least one pair $s \in S, t \in T, s \neq t$, such that a robot $r \in R$ placed in s overlaps with another robot $r' \in R$ placed in t . Thus, s, t cannot be in the same pumped configuration.

Fortunately, we can combine several graphs in order to find paths for more general unlabeled problems. For instance, robots may move from a pebble graph $G_S = (V, E)$ where $S \subset V$, through several other pebble graphs until they will finally reach $G_T = (V', E')$ where $T \subset V'$.

We first show that given two pebble graphs and an unlabeled path connecting two configurations, one from every graph, the robots can move from the first pebble graph to the second. This path serves as a “bridge” between the two graphs and connects not only the two configurations but many other configurations from the two graphs as well. Before describing a mechanism to generate such paths we provide a concrete description of the property discussed here in the form of the following lemma. We omit its proof, which is straightforward.

Lemma 2. *Let $C \subset V, C' \subset V'$ be two configurations of the pebble graphs $G = (V, E), G' = (V', E')$, respectively, and let $\pi_{C,C'}$ be a path for the unlabeled problem $\mathcal{U}' = (C, C')$. In addition, let D, D' be two configurations such that $D \subset V, D' \subset V'$ and $D \equiv C, D' \equiv C'$. Then there exists a path $\pi_{\mathcal{U}''}$ for $\mathcal{U}'' = (D, D')$.*

Paths similar to $\pi_{C,C'}$ described above are generated using the following component which generalizes the component *local planner* used in standard sampling-based algorithms. We postpone a detailed description of this component to Chapter 4.5.

Given two pumped configurations V, V' and an integer q , the *connection generator* returns q unlabeled paths such that every returned path $\pi_{C,C'}$ is a solution for some unlabeled problem $\mathcal{U}' = (C, C')$ where C, C' are configurations such that $C \subset V, C' \subset V'$.

By Lemma 2, a single connection implicitly connects a collection of configurations with a specific signature from the first graph with a similar collection in the second graph. We require from the connection generator to create several such connections in order to connect a variety of signatures between the two graphs.

4.4 Description of UPUMP

Next, we extend Lemma 2 to describe still more complex paths. The UPUMP algorithm has a preprocessing phase and a query phase. In the first phase it samples a collection of pebble graphs and connects them using the connection generator. Those connections represent edges in a roadmap \mathcal{H} whose vertices are configurations from the different pebble graphs. Additional edges, which represent paths between configurations within the same pebble graph, are added to \mathcal{H} afterwards. In the query phase, given start and target configurations S, T ,

UPUMP generates two pebble graphs that contain them. These two graphs are connected to other previously sampled pebble graphs. We give a more formal description below, along with the description of the parameters used by UPUMP.

Parameters. g is the number of sampled pebble graphs; n represents the size of a sampled pumped configuration; q is the maximal number of connections between two pebble graphs.

Preprocessing (Algorithm 3). UPUMP samples a collection \mathcal{G} of g pebble graphs (line 3). For every pair of sampled pebble graphs $G = (V, E), G' = (V', E')$ we apply the CONNECT procedure (line 6), which generates several connections between the two pebble graphs, and updates the roadmap accordingly. Then, we add edges to \mathcal{H} that represent connections that follow from Proposition 1 (line 8). Recall that two configurations are equivalent only if they were taken from the same pebble graph, and their signatures are identical. We add an edge between them but do not generate the respective paths at this point, as only some of them will eventually participate in a path returned in the query phase (an economical “lazy” approach).

Connect (Algorithm 4). This is an auxiliary method, which uses the connection generator component to connect two given pebble graphs (line 1). For every path $\pi_{C,C'}$ returned by the connection generator, where C, C' are configurations of G, G' , respectively, C and C' are added as vertices to the roadmap \mathcal{H} together with an edge between them. To this edge the information $\pi_{C,C'}$ is attached.

Query (Algorithm 5). In this phase, UPUMP is given the start and target configurations. As S, T can be considered as pumped configurations (containing m single-robot configurations) we generate the respective pebble graphs G_S, G_T (line 1). We then connect G_S, G_T to previously sampled pebble graphs using the connection generator and add relevant vertices and edges to \mathcal{H} (the CONNECT procedure described in Algorithm 4). Finally, if S, T are connected in \mathcal{H} a path retrieval is carried out.

Path Retrieval (Algorithm 6). Using a graph search algorithm, a path is found between S and T in \mathcal{H} (line 2). Then, it is transformed into a solution to the unlabeled problem $\mathcal{U} = (R, S, T)$. If two consecutive configurations C_{i-1}, C_i on the path are equivalent, then the respective pebble path is produced (line 6) and converted to a path for the unlabeled problem $\mathcal{U} = (R, C_{i-1}, C_i)$, following the process described in Proposition 1. If on the other hand $C_{i-1} \not\equiv C_i$, then the path π_{C_{i-1}, C_i} , that was generated by the connection generator, is used.

Algorithm 3 PREPROCESS(g, q, n)

- 1: $\mathcal{V} \leftarrow \emptyset; \mathcal{E} \leftarrow \emptyset; \mathcal{H} = (\mathcal{V}, \mathcal{E})$
- 2: $\mathcal{G} \leftarrow \emptyset$
- 3: **for** $i = 1 \rightarrow g$ **do**
- 4: $G \leftarrow \text{PEBBLE_GRAPH}(n)$
- 5: $\mathcal{G} \leftarrow \mathcal{G} \cup \{G\}$
- 6: **for all** $G, G' \in \mathcal{G}$ **do**
- 7: $\text{CONNECT}(G, G', q)$
- 8: **for all** $C, C' \in \mathcal{V}$ where $C \equiv C'$ **do**
- 9: $\mathcal{E} \leftarrow \mathcal{E} \cup \{(C, C')\}$

Algorithm 4 CONNECT($G = (V, E), G' = (V', E'), q$)

- 1: $\{(C_1, C'_1), \dots, (C_q, C'_q)\} \leftarrow \text{CONGEN}(V, V', q)$
- 2: **for** $i = 1 \rightarrow q$ **do**
- 3: $\mathcal{V} \leftarrow \mathcal{V} \cup \{C_i, C'_i\}$
- 4: $\mathcal{E} \leftarrow \mathcal{E} \cup \{(C_i, C'_i)\}$

Algorithm 5 QUERY(S, T, q)

- 1: $G_S = (S, \emptyset); G_T = (T, \emptyset)$
- 2: **for all** $G \in \mathcal{G}$ **do**
- 3: $\text{CONNECT}(G, G_S, q)$
- 4: $\text{CONNECT}(G, G_T, q)$
- 5: **if** S, T not connected in \mathcal{H} **then**
- 6: **return** FAILURE
- 7: **return** RETRIEVE_PATH(\mathcal{H}, S, T)

Algorithm 6 RETRIEVE_PATH(S, T)

- 1: $\Pi \leftarrow \emptyset$
- 2: $\{C_0, \dots, C_\ell\} \leftarrow \text{GRAPH_PATH}(\mathcal{H}, S, T)$
- 3: **for** $i = 1 \rightarrow \ell$ **do**
- 4: **if** $C_{i-1} \equiv C_i$ **then**
- 5: $G \leftarrow$ pebble graph of C_i
- 6: $\pi^* \leftarrow \text{PEBBLE_SOLVER}(G, C_{i-1}, C_i)$
- 7: $\pi \leftarrow \text{TRANSFORM_PATH}(\pi^*)$
- 8: $\Pi.\text{append}(\pi)$
- 9: **else**
- 10: $\Pi.\text{append}(\pi_{C_{i-1}, C_i})$
- 11: **return** Π

4.5 Algorithm for the Connection Generator

We describe an algorithm for the connection generator component (CONGEN), used by UPUMP. Recall that the connection generator is given two pumped configurations V, V' and an integer q that represents the number of desired connections. Throughout this section we will use the *local planner* mechanism, that was used in the implementation of the *edge planner* (Chapter 4.1). Recall that given two single-robot configurations $v, v' \in \mathcal{F}$ the local planner attempts to construct a path $\pi_{v,v'}$ for a robot $r \in R$ from v to v' .

The algorithm transforms the problem of finding paths between pumped configurations into the problem of finding an *independent set* in an undirected graph. We generate the set of pairs $\mathcal{L} = \{(v, v') | v \in V, v' \in V', \pi_{v,v'} \neq \perp\}$. Namely, these are pairs of elements from V, V' for which the local planner successfully generated a path. We say that two pairs $(v, v'), (u, u') \in \mathcal{L}$ *interfere* if there exists $\theta \in [0, 1]$ such that a robot $r \in R$ placed in $\pi_{v,v'}(\theta)$ collides with another robot $r' \in R$ placed in $\pi_{u,u'}(\theta)$. Notice that every two pairs $(v, v'), (u, u') \in \mathcal{L}$, such that $v = u$ or $v' = u'$, interfere by definition. We construct the *interference graph* \mathcal{I} whose vertices are the elements of \mathcal{L} , i.e., every vertex of \mathcal{I} represents a path. We connect a pair of vertices of \mathcal{I} by an edge if they interfere.

Notice that by definition, every independent set of size m of the vertices of \mathcal{I} represents a collection of m non-colliding single-robot paths. Note that the problem of finding an independent set is known to be NP-Hard.

We use the following heuristic to find several independent sets: vertices of the graph are examined one by one, the order is determined by a random permutation of the vertices. A new vertex is added to the set only if it is not connected to other vertices that are already in the set.

Remark. We concede that our approach to finding an independent set is not guaranteed to find a solution. This may impede attempts to prove the completeness of the UPUMP algorithm. We address this issue in Chapter 6 and state the modification that could lead to a probabilistic completeness proof of UPUMP.

5

Algorithm for the k -Color Case

We describe the changes required to transform UPUMP into KPUMP—an algorithm for the k -color problem. We stress that the extension to the k -color case is straightforward and we provide it here only for the completeness of presentation. KPUMP simultaneously samples several pumped configurations—each corresponds to a different color and hence to a different unlabeled problem. The resulting pebble graphs are constructed in a manner that prevents collision between robots of different colors. This calls for the redefinition of the edge planner mechanism (Chapter 4) as well as other components.

5.1 Composite Pebble Graphs

We begin with several definitions, which extend the primitives presented in the description of UPUMP. Recall that the k -color problem \mathcal{L} is defined by $\mathcal{U}_1, \dots, \mathcal{U}_k$ where each $\mathcal{U}_i = (R_i, S_i, T_i)$ is an unlabeled problem and $|R_i| = m_i$.

Definition 4. Let $\mathbb{C} = \{C_1, \dots, C_k\}$ be a collection of k configurations, where C_i is a configuration of \mathcal{U}_i . \mathbb{C} is a *composite configuration* if for every $c \in C_i, c' \in C_j$, where $i \neq j$, it holds that $R_i(c) \cap R_j(c') = \emptyset$.

Definition 5. Let $\mathbb{V} = \{V_1, \dots, V_k\}$ be a collection of pumped configurations, where V_i is a pumped configuration for \mathcal{U}_i . \mathbb{V} is a *composite pumped configuration* if every $\mathbb{C} = \{C_1, \dots, C_k\}$, such that $|C_i| = m_i$ and $C_i \subset V_i$, is a composite configuration.

Let \mathbb{V} be a composite pumped configuration, as defined above. We construct a pebble graph for every pumped configuration V_i of \mathbb{V} . The edges of every graph are generated in a similar manner to the unlabeled case, although here we impose more restrictions to avoid the collision between robots of different colors.

Next, we generate the *composite pebble graph* $\mathbb{G} = \{G_1, \dots, G_k\}$, where G_i is the pebble graph that resulted from the pumped configuration V_i . We now define an equivalence relation between composite configurations of the same composite pebble graph. Recall that two configurations are equivalent, if their signatures are identical (Definition 2). We generalize this notion for the case of composite configurations.

Definition 6. Let $\mathbb{G} = \{G_1, \dots, G_k\}$ be a composite pebble graph, where $G_i = (V_i, E_i)$. Let $\mathbb{C} = \{C_1, \dots, C_k\}, \mathbb{C}' = \{C'_1, \dots, C'_k\}$ be two composite configurations, where $C_i, C'_i \subset V_i$. We say that \mathbb{C} and \mathbb{C}' are *equivalent*, and denote this relation by $\mathbb{C} \equiv \mathbb{C}'$, if for every $1 \leq i \leq k$ it holds that $C_i \equiv C'_i$, where the latter “ \equiv ” symbol represents the equivalence relation between configurations.

The following proposition is a generalization of Proposition 1 and its proof is omitted as it is similar to the proof for the unlabeled case.

Proposition 2. Let $\mathbb{C} = \{C_1, \dots, C_k\}, \mathbb{C}' = \{C'_1, \dots, C'_k\}$ be two composite configurations of the same composite pebble graph. If $\mathbb{C} \equiv \mathbb{C}'$ then there exists a solution to the k -color problem $\{\mathcal{U}'_1, \dots, \mathcal{U}'_k\}$, where $\mathcal{U}'_i = (R_i, C_i, C'_i)$.

5.2 Description of KPUMP

We describe the sampling-based algorithm for the k -color case. KPUMP constructs a roadmap \mathcal{H} whose vertices are composite configurations (recall that in UPUMP, the vertices of this roadmap were configurations). The edges of \mathcal{H} represent valid paths between composite configurations. These paths either connect equivalent composite configurations, as described in Proposition 2, or composite configurations from different composite graphs, where the latter paths are generated using the following mechanism, which is a generalization of the connection generator (Chapter 4.3). Given two composite pumped configurations, and an integer q , the *composite connection generator* returns a collection of q paths, for the k -color problem, between the two composite pumped configurations.

We now return to the description of KPUMP. KPUMP samples composite pumped configurations $\mathbb{V}_1, \mathbb{V}_2, \dots, \mathbb{V}_g$ and generates the respective composite pebble graphs $\mathbb{G}_1, \dots, \mathbb{G}_g$. Given a path between two composite configurations \mathbb{C}, \mathbb{C}' returned by the composite connection generator we add the vertices \mathbb{C}, \mathbb{C}' to \mathcal{H} and the respective edge. Finally we connect the start and target composite configurations \mathbb{S}, \mathbb{T} , respectively, to previously sampled composite pebble graphs.

6

Toward Probabilistic Completeness of UPUMP

We show that by making a simple assumption on the work of the connection generator, it can be proved that UPUMP is probabilistically complete. In order to do so we show that a simplified version of the UPUMP algorithm, called UBASIC, is probabilistically complete. Its samples consist of pumped configurations of size m (as opposed to size $n > m$ in Chapter 4) which result in *degenerate* pebble graphs where the number of vertices is equal to the number of pebbles. We prove the completeness of UBASIC by showing a reduction from the PRM algorithm for the fully-colored multi-robot motion planning problem. The completeness of UPUMP follows as a rather straightforward corollary.

We stress that it still might be possible that UPUMP (and KPUMP), in its original formulation, is probabilistically complete, and we hope that the efforts made in this chapter will ultimately assist in proving this.

6.1 The PRM Algorithm for the Fully-Colored Case

The PRM algorithm was initially designed to solve single-robot motion planning problems. However, it can be used for solving the fully-colored multi-robot motion planning problem by considering the fleet of robots as one composite robot. We briefly describe the PRM algorithm for the fully-colored case. Recall that in the fully-colored problem, every robot r_i is assigned with specific start and target positions s_i, t_i . For the purpose of the probabilistic completeness proof of UPUMP, we may assume that the robots are geometrically identical.

Recall that the PRM algorithm for the single-robot case consists of two main phases. In the preprocessing phase the algorithm samples a collection of valid single-robot configurations. Then, for every sampled single-robot configuration it finds its nearest neighbors and tries to connect it to the neighbors using the local planner. In the query phase, the start and target single-robot configurations are connected to the constructed roadmap by considering

connections to the nearest neighbors of the start and target, respectively. We intentionally avoid from referring to a specific neighbor finding technique since there are several methods that are suitable for this task. Our only requirement from the neighbor-finding technique is that it will lead to a probabilistically complete PRM algorithm. Such methods are described in the work of Karaman and Frazzoli [12], where the issue of completeness is discussed as well.

In the case of the fully-colored multi-robot motion planning problem, every sample of the PRM consists of m single-robot configurations, one single-robot configuration for every robot. In contrast with the unlabeled case, where every robot can be assigned with any single-robot configuration, here every single-robot configuration is associated with a specific robot. This is formalized in the following definition.

Definition 7. Let $C = \{c_1, \dots, c_m\}$ be a configuration and let σ be some permutation of $\{1, \dots, m\}$. The *ordered configuration* of C for the permutation σ is defined to be $\sigma(C) = (c_{\sigma(1)}, \dots, c_{\sigma(m)})$.

We denote by σ_I the *identity permutation*. In an ordered configuration $\sigma(C)$ a position of the robot r_i is represented by $c_{\sigma(i)}$. Hence, the samples of the PRM algorithm for the fully-colored case are ordered configurations. For simplicity, we may assume that a configuration is sampled and a specific permutation σ_{PRM} is assigned to it. A connection between two ordered configuration is achieved by applying the *multi-robot local planner*. This component returns a set of m paths between two ordered configuration (if they exist), one for each robot, such that they are all collision free, both with respect to the obstacles and with respect to the other robots.

Definition 8. Let $\sigma(C) = (c_1, \dots, c_m), \sigma'(C') = (c'_1, \dots, c'_m)$ be two ordered configurations. Denote by π_i the path returned by the local planner (Chapter 4.1) on the input c_i, c'_i . Suppose that for every i , it holds that $\pi_i \neq \perp$, namely, the local planner successfully generated a path for the input c_i, c'_i . In addition, suppose that every pair of paths π_i, π_j is collision free, i.e., for every $\theta \in [0, 1]$, $r(\pi_i(\theta)) \cap r(\pi_j(\theta)) = \emptyset$, where $r(c)$, for $c \in \mathcal{C}$, represents the portion of the configuration space that is covered by the robot that is placed in c (Chapter 2). Then the *multi-robot local planner* returns the set of paths $\{\pi_1, \dots, \pi_m\}$. Otherwise, it returns \perp .

If the multi-robot local planner successfully connects two ordered configurations, then an edge between them is added to the PRM roadmap. We summarize the steps of the PRM algorithm for the fully-colored problem. In the *preprocessing* phase, PRM samples a collection of ordered configurations $\{\sigma_{\text{PRM}}(C_1), \dots, \sigma_{\text{PRM}}(C_g)\}$. Then, for every sampled ordered configuration it finds a set of neighbors and attempts to connect them with the current sample. We refer to the roadmap that results from this process as the *induced roadmap* of the samples $\sigma_{\text{PRM}}(C_1), \dots, \sigma_{\text{PRM}}(C_g)$. In the *query phase*, the PRM algorithm is given two ordered configurations $(s_1, \dots, s_m), (t_1, \dots, t_m)$, and attempts to connect them to the roadmap. The following theorem is a generalization of the completeness theorem for the single-robot case [12].

Theorem 1. Let $\{\mathcal{U}_1, \dots, \mathcal{U}_m\}$ be a fully-colored problem where $\mathcal{U}_i = (r_i, s_i, t_i)$ for which there is a solution. Then there exist constants $a > 0, g_0 \in \mathbb{N}$, such that a PRM algorithm with $g > g_0$ samples will find a solution with probability at least $1 - e^{-ag}$.

6.2 The UBASIC Algorithm

We present the UBASIC algorithm, which is a simplified version of the UPUMP algorithm. The pseudo-code of UBASIC is identical to the one described for UPUMP in Chapter 4. However, we set the number of vertices of the sampled pebble graphs to be m , i.e., we assign $n := m$. This forces Algorithm 2 to generate configurations, instead of pumped configurations. In order to show that UBASIC is complete, we enforce an additional constraint on the connection generator. It is described next.

Recall that the connection generator transforms the task of pathfinding between two pumped configurations to the problem of finding an independent set of size m , that represents a set of non-colliding paths, in the interference graph \mathcal{I} (Chapter 4.5). Currently, the independent sets in \mathcal{I} are found using a greedy technique, which is not guaranteed to find a solution, even if one exists. We will introduce below an additional step to the connection generator that is guaranteed to find at least one solution, if exists. For now, we assume that the following assumption holds. We will discuss its impact on UPUMP later on.

Assumption 1. Let C, C' be two configurations. Suppose that there exist two permutations, σ, σ' , for which the multi-robot local planner finds a path for the input $\sigma(C), \sigma'(C')$. Then, upon the application of the connection generator on the input C, C' , it returns at least one path $\pi_{C, C'}$, that is a solution to the unlabeled problem $\mathcal{U}' = (C, C')$.

Notice that we do not insist that the connection generator will return exactly the same path that was generated by the multi-robot local planner. The following observation shows that an unlabeled problem has a solution if and only if there exists a solution to some fully-colored problem from a family of problems. It is a crucial component in the probabilistic completeness proof of the UBASIC algorithm.

Observation 1. Let $\mathcal{U} = (R, S, T)$ be an unlabeled problem, where $R = \{r_1, \dots, r_m\}, S = \{s_1, \dots, s_m\}, T = \{t_1, \dots, t_m\}$. There is a solution to \mathcal{U} if and only if there exists a permutation σ_T , such that there is a solution to the fully-colored problem $\mathcal{L} = \{\mathcal{U}_1, \dots, \mathcal{U}_m\}$, where $\mathcal{U}_i = (r_i, s_i, t'_i)$ and $\sigma_T(T) = (t'_1, \dots, t'_m)$.

Lemma 3. Let C_1, \dots, C_g be a collection of configurations sampled by UBASIC in the pre-processing stage. Denote by G_{PRM} the PRM roadmap that is induced by the collection of PRM samples $\sigma_{PRM}(C_1), \dots, \sigma_{PRM}(C_g)$. Suppose that there exists a permutation σ_T for which the PRM algorithm, with the roadmap G_{PRM} , finds a solution for the query $\sigma_I(S), \sigma_T(T)$ (where σ_I is the identity permutation). Then, UBASIC will successfully find a solution for the query (S, T) .

Proof. Denote by $\sigma_I(S) = \sigma_I(C_0), \sigma_{PRM}(C_1), \dots, \sigma_{PRM}(C_{\ell-1}), \sigma_T(C_\ell) = \sigma_T(T)$, the path that was found by the PRM roadmap G_{PRM} after connecting the query $\sigma_I(S), \sigma_T(T)$. Thus, the multi-robot local planner successfully connected every pair of consecutive ordered configurations $\sigma_{PRM}(C_i), \sigma_{PRM}(C_{i+1})$ along the path (the same applies to the ends of the path). By Assumption 1, we deduce that the connection generator successfully connects C_i, C_{i+1} . Thus, C_i, C_{i+1} are connected in the roadmap \mathcal{H} in the UBASIC algorithm. \square

Using this connection between PRM and UBASIC we show that the latter is probabilistically complete.

Theorem 2. *Let $\mathcal{U} = (R, S, T)$ be an unlabeled problem for which there is a solution. Then there exist constants $a > 0, g_0 \in \mathbb{N}$, such that the UBASIC algorithm with $g > g_0$ samples will find a solution with probability at least $1 - e^{-ag}$.*

Proof. By Observation 1, there exists a permutation σ_T for which there is a solution to the fully colored problem $\mathcal{L} = \{\mathcal{U}_1, \dots, \mathcal{U}_m\}$, where $\mathcal{U}_i = (r_i, s_i, t'_i)$ and $\sigma_T(T) = (t'_1, \dots, t'_m)$. Let C_1, \dots, C_g be the collection of the g configurations sampled by UBASIC. By Theorem 1, the PRM algorithm, with the roadmap induced by the samples $\sigma_{\text{PRM}}(C_1), \dots, \sigma_{\text{PRM}}(C_g)$, will find a solution for the query $\sigma_I(S), \sigma_T(T)$, with probability at least $1 - e^{-ag}$. If the latter occurs, then by Lemma 4, UBASIC finds a solution as well. Thus, UPUMP finds a solution with probability at least $1 - e^{-ag}$. \square

6.3 Extending Completeness to UPUMP

We force UPUMP to generate a roadmap that simulates a run of the UBASIC, by modifying Assumption 1. Recall, that in the UPUMP algorithm, the connection generator is applied on pumped configurations (and not configurations, as in UBASIC).

Let $V = \{v_1, \dots, v_n\}$ be a pumped configuration. Denote by $V(m)$ the configuration that consists the first m elements of V .

Assumption 2. Let V, V' be two pumped configurations. Suppose that there exist two permutations, σ, σ' , for which the multi-robot local planner finds a path for the input $\sigma(V(m)), \sigma'(V'(m))$. Then, upon the application of the connection generator on the input pumped configurations V, V' , it must return at least one path $\pi_{V, V'}$, that is a solution to the unlabeled problem $\mathcal{U}' = (V, V')$.

Under this Assumption 2, we extend Lemma 4 for the UPUMP algorithm.

Lemma 4. *Let G_1, \dots, G_g be a collection of pebble graphs sampled by UPUMP in the pre-processing stage, where $G_i = (V_i, E_i)$, and V_i is a pumped configuration. Denote by G_{PRM} the PRM roadmap that is induced by the collection of PRM samples $\sigma_{\text{PRM}}(V_1(m)), \dots, \sigma_{\text{PRM}}(V_g(m))$. Suppose that there exists a permutation σ_T for which the PRM algorithm, with the roadmap G_{PRM} , finds a solution for the query $\sigma_I(S), \sigma_T(T)$. Then, UPUMP will successfully find a solution for the query (S, T) .*

The proof is trivial, and hence omitted. The following corollary immediately follows.

Corollary 1. *Let $\mathcal{U} = (R, S, T)$ be an unlabeled problem for which there is a solution. Then there exist constants $a > 0, g_0 \in \mathbb{N}$, such that the UPUMP algorithm with $g > g_0$ samples of pebble graphs will find a solution with probability at least $1 - e^{-ag}$.*

6.4 Reinforcing the Connection Generator

As mentioned earlier, in its current state (as described in Chapter 4.5) the connection generator does not fulfil the requirement of Assumption 1. Thus, a modification of the component is required if we wish guarantee the correctness of Theorem 2.

We describe a simple alternative implementation of the connection generator component that is based on *integer programming* (IP) and guarantees to find a connection if one exists, thus fulfilling Assumption 1.

Recall that in UBASIC the connection generator is given two configurations $V = \{v_1, \dots, v_m\}$, $V' = \{v'_1, \dots, v'_m\}$. In addition, recall that $\mathcal{L} = \{(v, v') | v \in V, v' \in V', \pi_{v, v'} \neq \perp\}$ is the set of all pairs of elements from V, V' for which the local planner successfully generated a path. To every pair $(v, v') \in \mathcal{L}$ we assign the boolean variable $x_{v, v'} \in \{0, 1\}$ that indicates whether the respective path is selected for the connection. Our goal is to find m non-interfering pairs. This results in the following two constraints.

1. If $(v, v'), (u, u') \in \mathcal{L}$ *interfere* then $x_{v, v'} + x_{u, u'} \leq 1$.
2. $\sum_{(v, v') \in \mathcal{L}} x_{v, v'} = m$.

We mention that although the problem of integer programming is known to be NP-hard, in practice these problems can be solved efficiently using various software packages, e.g., [6].

7

Experimental Results

We describe experimental results for the case of disc robots in the plane moving amidst polygonal obstacles. We show results for five challenging scenarios and compare the performance of KPUMP with two other sampling-based algorithms. Specifically we compare KPUMP with the PRM implementation of the OOPSMP package [23] on inputs of the fully-colored problem. For other inputs we use a basic sampling-based algorithm for the k -color problem called KBASIC, which is an extension of the UBASIC, described in the previous chapter.

KPUMP was implemented in C++ using CGAL Arrangements [7] and the Boost Graph Library (BGL) [26]. The code was tested on a PC with Intel i7-2600 3.40GHz processor with 8GB of memory, running a Windows 7 64-bit OS. For the implementation of the *local planner*, which attempts to connect two single-robot configurations with a simple path, a straight-line connection strategy [1] was used. This strategy attempts to move a robot along a straight line drawn between two single-robot configurations.

Parameters of KPUMP. The algorithm has three parameters that affect its performance: g describes the number of the sampled pebble graphs in the UPUMP algorithm, or the number of composite pebble graphs in KPUMP; q is the number of connections produced by the connection generator between two samples; μ is the maximal number of single-robot configurations that one sample comprises, i.e., for every sampled pumped configuration $\mathbb{V} = \{V_1, \dots, V_k\}$ it holds that $\sum |V_i| \leq \mu$. The value of the latter parameter depends on the input problem. For unlabeled problems, increasing μ results in increased connectivity of the resulting pebble graphs. Thus, it will be beneficial that the pumped configurations will be as large as possible (limited by the geometry of the scenario). On the other hand, in k -colored problems, where $k > 1$ the value μ has to be set more carefully as an excessively high value of μ will reduce the connectivity of the pebble graphs. This stems from the fact that a single-robot path produced by the edge planner has to avoid collision with robots from other groups. Consequently, as the value of μ grows it becomes harder to connect single-robot

configurations using an edge planner.

Test Scenarios. The scenarios are illustrated in Figure 7.1 and represent a variety of challenging problems. The unlabeled problem in (a) involves the motion of a large collection of robots. Scenarios (b) and (e) describe 2-color and 4-color problems comprising a large number of robots as well. Although scenarios (c), (d) do not involve as many robots, they are nevertheless challenging. This range of problems demonstrate the work of the various components of the KPUMP algorithm. In the first three scenarios the resulting pebble graphs have a low number of connected components due to the low value of k (as in scenario (a)) or high clearance from the obstacles (as in (e)). Therefore, large portions of the resulting paths involve the motions of the robots on paths induced by pebble problems. While the generated graphs in scenarios (c) and (d) have low connectivity, KPUMP still performs well—due to the use of the connection generator.

The results of running KPUMP for specific parameters are given in Table 7.1. In addition to the parameters mentioned above, the table contains the values k for the number of colors, m the number of robots in every color and M the total number of robots. The running times are given in seconds and represent the overall duration of the preprocessing and query phases, for a single query. The parameters used by KPUMP and other algorithms, mentioned later on, were manually optimized over a concrete set. A failure was declared when an algorithm was unable to solve a scenario for more than three runs out of five.

Table 7.1: Results for selected scenarios.

	Properties			Parameters			Time (secs)
	k	m	M	g	q	μ	
(a)	1	25	25	2	5000	150	23.2
(b)	2	8	16	50	1000	40	20.3
(c)	8	1	8	100	150	32	213.7
(d)	5	1	5	50	100	25	1.9
(e)	4	3	12	40	250	28	32.9

Comparison with Other Algorithms. The first part of the comparison involves solely inputs of the fully-colored problem. We compare KPUMP with the implementation of PRM provided by OOPSMP, which, by our experience, is very efficient. This algorithm is designed for solving fully-colored multi-robot motion planning problems. While OOPSMP required 100 seconds to solve scenario (d), KPUMP managed to solve it in 1.9 seconds. Scenario (c) proved to be even more challenging for OOPSMP, which failed to solve it, even when was given 5000 seconds of preprocessing time, whereas KPUMP solved in 213.7 seconds.

In order to provide a more informative comparison, we ran both algorithms on scenarios (c),(d), only that now we increased the difficulty of these scenarios gradually—incrementally introducing the robots, i.e., starting with a single robot and adding the others one by one, as long as OOPSMP succeeded solving the new inputs in reasonable time. In this case OOPSMP was able to solve scenario (c) with five robots, while the case of six robots was out of its reach (when given 5000 seconds of preprocessing time). The speedup of KPUMP compared to OOPSMP for this new range of scenarios is depicted in Figure 7.2 along with an additional test case (“decoupled-simple”), which is a simpler variant of scenario (c) with some of the obstacles removed and the radius of the robots decreased. The latter was designed to test the performance of OOPSMP on problems involving a higher number of robots.

As we are not aware of any other algorithms for the k -color problem, we designed a basic

algorithm to compare KPUMP with. This algorithm, which we call KBASIC, is a special case of KPUMP that samples configurations, instead of pumped configurations, and can be viewed as an extension of PRM for the k -color case (for more details, see Chapter 6). The entire set of scenarios (a)-(e),(a*)-(d*), in their original form, proved to be too challenging for KBASIC, which spent at times more than ten minutes in typical runs. Similarly to the previous comparison we designed a set of simple test scenarios. Specifically, scenario (e) was converted into five k -color problems for $1 \leq k \leq 5$ by partitioning the robots into k groups such that robot number i was assigned to the group $i \bmod k$. Then, as in the previous comparison, the robots were introduced incrementally. Figure 7.2 depicts the speedup of KPUMP compared with KBASIC for each of the k -color problems. This shows that KPUMP outperforms KBASIC in every possible setting, be it a k -color, unlabeled or fully-colored problem.

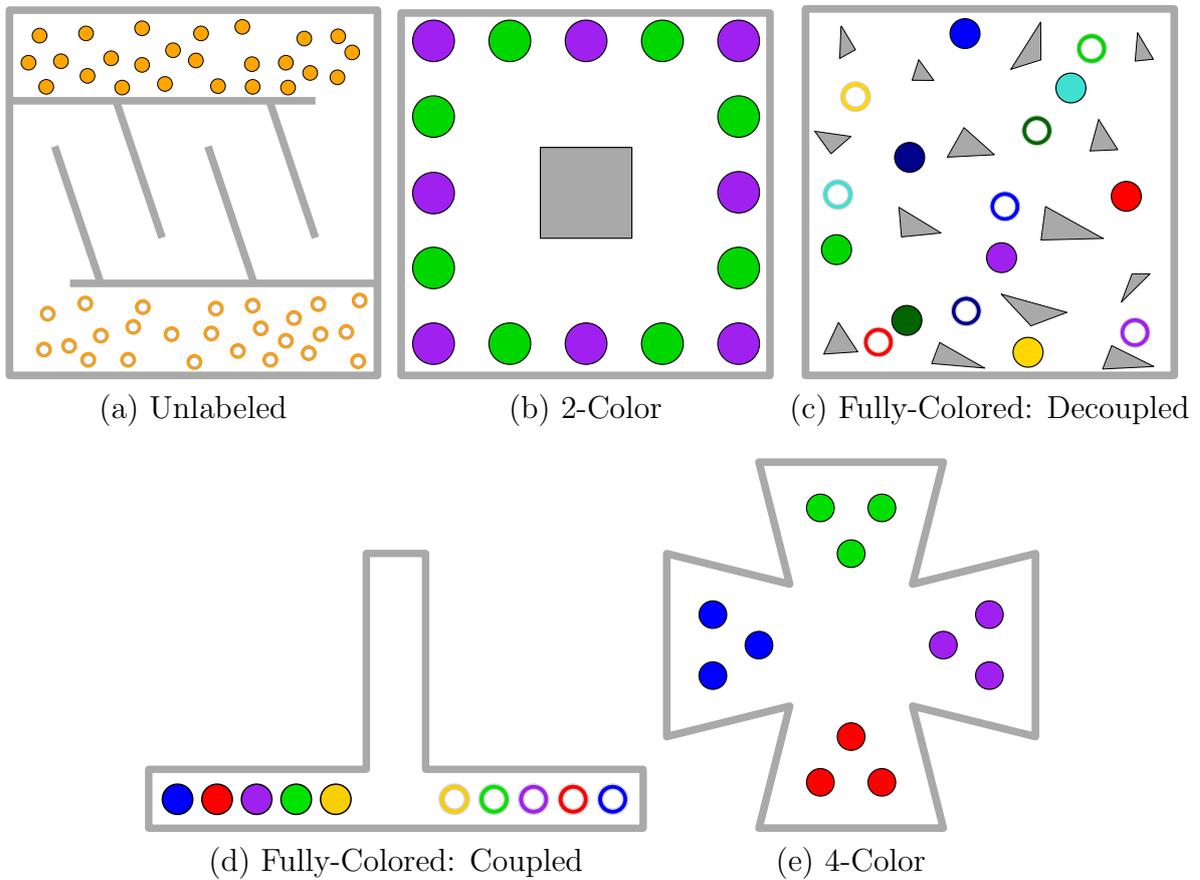


Figure 7.1: [Best viewed in color] Start positions of the robots are indicated by discs while target positions are illustrated as circles in respective colors (unless otherwise indicated). (a) Unlabeled scene with twenty five robots. (b) 2-Color scene; the two groups are required to switch positions. (c) Fully-colored scene with eight robots. (d) Fully-colored scene with five robots. (e) 4-Color scene; every group has to move in a clockwise manner to the next room, e.g., the blue group should move to the top room.

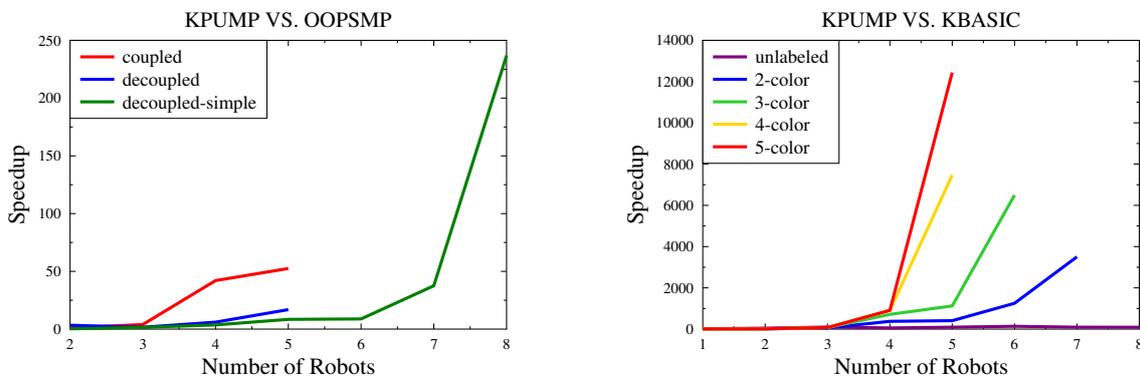


Figure 7.2: [Best viewed in color] Comparing KPUMP with OOPSMP/PRM and KBASIC.

8

Discussion and Further Work

In this chapter we discuss the various properties of the KPUMP algorithm and novelties it encompasses, as well as directions for future research.

8.1 Shortcomings of the Composite Robot Approach

While the composite robot approach usually leads to probabilistically complete algorithms, a property which is not provided in decoupled planners, it suffers from inefficiency. The traditional composite robot approach to the multi-robot problem treats the group of robots as one composite robot whose configuration space is the Cartesian product of the configuration spaces of the individual robots. With this approach, single-robot tools, such as sampling-based algorithms, can be used to solve multi-robot problems. For instance, this technique is used in the software packages OOPSMP and OMPL [14, 23] where PRM is applied to the fully-colored problem, and in the KBASIC algorithm discussed above. Paths generated by this approach usually force the robots to move simultaneously from one placement to the other, where none of the robots remains in the same position while the others are moving.

We believe that such paths are unnatural in the multi-robot setting and are more difficult to produce than paths that involve motion of only few robots at a time. Given collision-free placements for all the robots it is usually possible to move some of the robots to different placements without altering the placements of the rest of the robots, i.e., those robots remain still. For instance, consider a configuration $C = \{c_1, \dots, c_m\}$ for some unlabeled problem \mathcal{U} with m robots. Unless the workspace is extremely tight, another configuration C' can be derived from C where only c_1 is moved to c'_1 . Moreover, connecting two such configurations by a path requires only a single-robot collision-free path for which the moving robot does not collide with the other robots placed in c_2, \dots, c_m . In contrast, the connection of two “unrelated” configurations by a path imposes much harder constraints— m single-robot

collision-free paths have to be created and in addition, robots moving along those paths must not collide with each other.

KPUMP utilizes this observation by restricting the movements of the robots along certain path sections—induced by pebble problems—to motions of individual robots. We emphasize that KPUMP does not preclude simultaneous movements of robots when necessary, specifically on path sections where the robots move from one pebble graph to the other along paths generated by the connection generator.

8.2 Amplification of Samples

Pumped configurations that are sampled by KPUMP, and the resulting pebble graphs, are fairly simple structures which require only little effort to generate. Yet, using the transformation to pebble problems, these samples are amplified to describe not only placements and paths for single robots, but also to represent an incredible amount of paths and positions for all the robots in a given problem. However, this information is not represented explicitly and only little storage space is required to represent a pebble graph. In addition, a small number of configurations must be stored. Specifically, these are configurations through which the pebble graphs connects to other graphs. Such configurations are selected by the *connection generator*. Similarly, this component does not require an explicit representation of all the configurations represented by the pebble graph. Furthermore, continuing the theme presented here that one action leads to a large number of outcomes, namely, a sample of a pumped configuration results in many configurations, a path generated by a connection generator not only connects two configurations from the two pebble graphs, but also a large number of configurations from them, which are not necessarily directly connected. Thus, these properties enable KPUMP to generate a variety of configurations and motions of the robots, using only few samples. To reproduce this variety by KBASIC one must generate far more samples.

An additional advantage of the use of pebble graphs lies in the fact that they can be connected more easily than two configurations, when a powerful component as the connection generator is at hand. Using this component, KPUMP succeeds in solving difficult scenarios even when generated pebble graphs suffer from low connectivity, as in the scenarios (c) and (d), depicted in Figure 7.1.

8.3 Further Work

Our immediate future goal is to investigate the completeness of the original formulation of the algorithm, i.e., using the connection generator algorithm that appears in Chapter 4. In addition, it would be interesting to apply KPUMP to problems that involve more complex robots (e.g., rotating and translating polygons in the plane, multi-joint robots). The experiments carried in this work suggest that the k -color problem, for various values of k , is less challenging than a fully-colored problem (with the same number of robots). Hence, it may be interesting to investigate the computational complexity of the unlabeled and k -color problems.

Bibliography

- [1] Nancy M. Amato, O. Burçhan Bayazit, Lucia K. Dale, Christopher Jones, and Daniel Vallejo. Choosing good distance metrics and local planners for probabilistic roadmap methods. *IEEE Transactions on Robotics*, 16(4):442–447, 2000.
- [2] Boris Aronov, Mark de Berg, A. Frank van der Stappen, Petr Švestka, and Jules Vleugels. Motion planning for multiple robots. *Discrete & Computational Geometry*, 22(4):505–525, 1999.
- [3] Vincenzo Auletta, Angelo Monti, Mimmo Parente, and Pino Persiano. A linear time algorithm for the feasibility of pebble motion on trees. In *Scandinavian Symposium and Workshops on Algorithm Theory (SWAT)*, pages 259–270, 1996.
- [4] Gruia Calinescu, Adrian Dumitrescu, and János Pach. Reconfigurations in graphs and grids. *SIAM Journal on Discrete Mathematics*, 22(1):124–138, 2008.
- [5] Howie Choset, Kevin M. Lynch, Seth Hutchinson, George A Kantor, Wolfram Burgard, Lydia E. Kavraki, and Sebastian Thrun. *Principles of Robot Motion: Theory, Algorithms, and Implementations*. MIT Press, 2005.
- [6] I. CPLEX. 11.0 users manual. *ILOG CPLEX Division. Incline Village, NV*, 2007.
- [7] Efi Fogel, Dan Halperin, and Ron Wein. *CGAL Arrangements and Their Applications: A Step-by-Step Guide*. Geometry and Computing. Springer, 2012.
- [8] Oded Goldreich. Shortest move-sequence in the generalized 15-puzzle is NP-hard. *Manuscript, Laboratory for Computer Science, MIT*, 1, 1984.
- [9] Gilad Goraly and Refael Hassin. Multi-color pebble motion on graphs. *Algorithmica*, 58(3):610–636, 2010.

- [10] Shai Hirsch and Dan Halperin. Hybrid motion planning: Coordinating two discs moving among polygonal obstacles in the plane. In *Workshop on the Algorithmic Foundations of Robotics (WAFR)*, pages 239–255. Springer, 2002.
- [11] John E. Hopcroft, Jacob T. Schwartz, and Micha Sharir. On the complexity of motion planning for multiple independent objects: PSPACE-hardness of the “Warehouseman’s problem”. *International Journal of Robotics Research*, 3(4):76–88, 1984.
- [12] Sertac Karaman and Emilio Frazzoli. Sampling-based algorithms for optimal motion planning. *International Journal of Robotics Research*, 30(7):846–894, 2011.
- [13] Lydia Kavraki, Petr Švestka, Jean claude Latombe, and Mark Overmars. Probabilistic roadmaps for path planning in high dimensional configuration spaces. *IEEE Transactions on Robotics and Automation*, 12(4):566–580, 1996.
- [14] Kavraki Lab. The open motion planning library (OMPL), 2010. ompl.kavrakilab.org.
- [15] Daniel Kornhauser. Coordinating pebble motion on graphs, the diameter of permutation groups, and applications. M.Sc. thesis, Department of Electrical Engineering and Computer Scienc, Massachusetts Institute of Technology, 1984.
- [16] Daniel Kornhauser, Gary L. Miller, and Paul G. Spirakis. Coordinating pebble motion on graphs, the diameter of permutation groups, and applications. In *Foundations of Computer Science (FOCS)*, pages 241–250. IEEE Computer Society, 1984.
- [17] James Kuffner and Steven M. LaValle. RRT-connect: An efficient approach to single-query path planning. In *International Conference on Robotics and Automation (IROS)*, volume 2, pages 995 –1001 vol.2, 2000.
- [18] Steven M. LaValle. *Planning Algorithms*. Cambridge University Press, 2006.
- [19] Stéphane Leroy, Jean-Paul Laumond, and Thierry Siméon. Multiple path coordination for mobile robots: A geometric algorithm. In *International Joint Conference on Artificial Intelligence*, pages 1118–1123, 1999.
- [20] Sam Loyd. *Mathematical Puzzles of Sam Loyd*. Dover, 1959.
- [21] Ryan Luna and Kostas E. Bekris. Efficient and complete centralized multi-robot path planning. In *International Conference on Intelligent Robots and Systems (IROS)*, pages 3268–3275, 2011.

- [22] Christos H. Papadimitriou, Prabhakar Raghavan, Madhu Sudan, and Hisao Tamaki. Motion planning on a graph (extended abstract). In *Foundations of Computer Science (FOCS)*, pages 511–520, 1994.
- [23] Erion Plaku, Kostas E Bekris, and Lydia E Kavraki. OOPS for motion planning: An online open-source programming system. In *International Conference on Robotics and Automation (ICRA)*, pages 3711–3716. IEEE, 2007.
- [24] Gildardo Sanchez and Jean-Claude Latombe. Using a PRM planner to compare centralized and decoupled planning for multi-robot systems. In *International Conference on Robotics and Automation (ICRA)*, pages 2112–2119, 2002.
- [25] Jacob T. Schwartz and Micha Sharir. On the piano movers’ problem: III. Coordinating the motion of several independent bodies. *International Journal of Robotics Research*, 2(3):46–75, 1983.
- [26] Jeremy Siek, Lie-Quan Lee, and Andrew Lumsdaine. Boost graph library. <http://www.boost.org/libs/graph/>, June 2000.
- [27] Jur van den Berg, Jack Snoeyink, Ming C. Lin, and Dinesh Manocha. Centralized path planning for multiple robots: Optimal decoupling into sequential plans. In *Robotics: Science and Systems (RSS)*, 2009.
- [28] Jur P. van den Berg and Mark H. Overmars. Prioritized motion planning for multiple robots. In *International Conference on Intelligent Robots and Systems (IROS)*, pages 430 – 435, 2005.
- [29] Petr Švestka and Mark H. Overmars. Coordinated path planning for multiple robots. *Robotics and Autonomous Systems*, 23:125–152, 1998.
- [30] Glenn Wagner and Howie Choset. M*: A complete multirobot path planning algorithm with performance bounds. In *International Conference on Intelligent Robots and Systems (IROS)*, pages 3260–3267, 2011.
- [31] Glenn Wagner, Minsu Kang, and Howie Choset. Probabilistic path planning for multiple robots with subdimensional expansion. In *International Conference on Robotics and Automation (ICRA)*, pages 2886–2892, 2012.
- [32] Richard M. Wilson. Graph puzzles, homotopy, and the alternating group. *Journal of Combinatorial Theory, Series B*, 16(1):86–96, 1974.

- [33] Jingjin Yu and Steven M. LaValle. Distance optimal formation control on graphs with a tight convergence time guarantee. In *IEEE International Conference on Decision and Control*, pages 4023–4028, 2012.