Deployment of Multi-Agent Pathfinding on a Swarm of Physical Robots
centralized control via reflex-based behavior

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Abstract: Multi-agent pathfinding is a problem of finding paths for multiple agents from their initial configuration to their goal configuration that results in a plan execution without collisions. In this paper, we deploy MAPF solutions on a swarm of small mobile robots. During the plan execution, we mitigate the problem of desynchronization that comes with the plan execution on physical hardware using the reflex-based behavior of the robots. Such deployment can help researchers and educators to demonstrate and test their findings in the physical world. The robot has a line-following capability that can be used for simulation of discrete MAPF solutions. The control curves are displayed in real-time on a display on which the robots move during their path execution. A prototype of the deployment was built and tested experimentally.

1 Introduction

Multi-agent pathfinding problem (MAPF) is the task of finding a plan that navigates multiple agents in an environment from their initial positions to their goal positions without them colliding during the execution [Kornhauser et al., 1984, Ryan, 2008, Sharon et al., 2015, Sharon et al., 2013, Silver, 2005, Surynek, 2009, Wang and Botea, 2011]. The environment is usually modeled as an undirected graph $G = (V, E)$ in which the agents move. In each vertex of G at most one agent is placed, and they can move across edges of the graph. At each time step agent can either *wait* in the current vertex or *move* to a neighboring one that is unoccupied. Some additional problem-specific models and constraints may be used for various applications.

Due to its real-world applications, MAPF has been a deeply researched topic over recent years. New variations of this problem and approaches to solving them, emerged, and new solving algorithms have been designed. Many practical problems from robotics can be interpreted as MAPF. Examples include item rearrangement in automated warehouses [Basile et al., 2012], ship collision avoidance [Kim et al., 2014], or formation maintenance and maneuvering of aerial vehicles [Zhou and Schwager, 2015].

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Crossing the gap between a virtual simulation of MAPF and physical hardware execution is not an easy task. Deployment in the physical world comes with additional problems and constraints for the system, and specialized solutions are often developed for these applications. Using existing solutions on physical robots is usually unattainable since most of the MAPF solutions produce discrete plans, and robotic hardware moves continuously in a continuous environment. The additional problem is that these solutions do not account for problems like desynchronization that occur in these physical deployments.

1.1 Contribution

This paper describes the deployment of discrete MAPF solutions on a swarm of small mobile robots– Ozobot Evo. Ozobot robots have a line following capabilities and are also programmable. The use of discrete MAPF models and limited hardware of the robots makes the system prone to desynchronization. We used the reflex-based behavior of the robots to control them on a surface of a display and mitigate the desynchronization. The navigation of the robots is provided by control curves that are displayed underneeth the robots during their plan execution.

This deployment brings a new approach to mitigation of desynchronization during plan execution and the execution of existing MAPF solutions on physical robots. Our contribution could also help researchers and educators to demonstrate theoretical MAPF solutions in the physical world.

The paper is organized as follows. First, we introduce MAPF formally and recall major solving algorithms. Then Ozobot Evo, a robot we use for simulation, is introduced. The previous MAPF deployment strategy on Ozobot is shortly described and used to test the susceptibility of the robot's hardware for desynchronization. Then we introduce a new strategy for MAPF deployment on the swarm of Ozobot Evo robots through reflex-based control, focusing on the mitigation of desynchronization. In the end, the implemented prototype is experimentally evaluated on various MAPF benchmarks, and the results are summarized.

2 Overview of MAPF

Almost all previous MAPF research and proposed solvers were built on top of several assumptions about time. First, time is not continuous, but rather *discretized* into time steps. Second, all actions that agents perform take the same amount of time to execute, precisely one time step. Moreover, a significant portion of the research was done on simple grid graphs, and agents are usually entities of the same shape and size that fit into one graph vertex. In [Andreychuk et al., 2019], the authors propose an algorithm that supports *continuous time* and agent actions of different durations. Agents even can have different speeds. The collision detection is geometry-aware so that the algorithm can handle agents of different sizes and shapes. The algorithm is optimal and complete.

Generally, there are three major categories of MAPF solvers–search-based, reduction-based, and rule-based. In the *search-based* category are algorithms like CBS [Sharon et al., 2015] and its improved variants [Boyarski et al., 2015], ICTS [Sharon et al., 2013], or other algorithms based on A*. *Reduction-based* solvers reduce the MAPF problem instance to an instance in a different paradigm for which an efficient solver exists. These solvers utilize reduction to SAT[2] problems [Surynek, 2012], answer set programming [Erdem et al., 2013] or integer linear programming [Yu and LaValle, 2013]. *Rule-based* solvers work with specific agent movement rules, and examples are the algorithms Push-and-Swap [Luna and Bekris, 2011a], BIBOX [Surynek, 2009], and Push-and-Rotate [de Wilde et al., 2014].

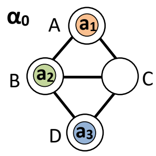
[2]Boolean satisfiability

Some other approaches have also been researched over the last years. Opposed to the *cooperative pathfinding* (CPF) [Silver, 2005, Jansen and Sturtevant, 2008], which is the same concept as the classical MAPF, where agents aim to fulfill one global goal as effectively as possible, there is *adversarial cooperative pathfinding*[3] (ACPF) [Ivanová and Surynek, 2013]. In ACPF, agents are divided into a finite number of teams that alter in turns between time steps. The goal of ACPF is to find a winning solution for one selected team of agents that reacts to moves of other, adversarial, groups of agents. Additionally, ACPF can follow different tactics like offense or defense. The adversarial approach to MAPF provided additional opportunities for future research.

2.1 Classical Discrete MAPF

The classical MAPF problem [Silver, 2005, Ryan, 2008] consists of an undirected graph $G = (V, E)$ and a set of agents $A = \{a_1, a_2, ..., a_k\}$ such that $|A| < |V|$. Agents are placed in the vertices so that at most one agent resides in each vertex. The configuration of agents is denoted $\alpha : A \rightarrow V$. Next, we are given the initial configuration of the agents α_0 and goal configuration α_+.

At each time step of the solution, every agent has two possible actions from which it can choose. The agent can either *wait* in its current vertex or *move* to one of the neighboring vertices if the move is allowed. In classical MAPF, these are the only two actions that agents can perform. The task is to find a sequence of such actions for each agent a_i that moves the agent from $\alpha_0(a_i)$ to $\alpha_+(a_i)$ such that agents do not *collide*, i.e., do not occupy the same vertex simultaneously. Typically, an agent can enter only currently unoccupied vertices. In other words, moving into a vertex, from which another agent is leaving, is not considered an allowed move. An example of a MAPF instance is shown in Figure 1.



	α_0	α_1	α_2	α_3	$\alpha_4 = \alpha_+$
a_1	A	C	C	C	D
a_2	B	B	A	A	A
a_3	D	D	D	B	B

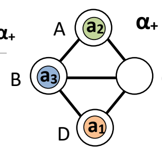


Figure 1: A MAPF instance with three agents a_1, a_2, and a_3.

Below, we define a *move-to-unoccupied* variant of MAPF, where agents are allowed to move only to unoccupied vertices.

[3]Adversarial cooperative pathfinding can also be referred to as adversarial pathfinding or adversarial MAPF.

Definition 1. (Move-to-unoccupied MAPF). *Configuration α' results from α if and only if the following conditions hold:*

(i) $\alpha(a) = \alpha'(a)$ or $\{\alpha(a), \alpha'(a)\} \in E$ for all $a \in A$ (agents wait or move along edges);

(ii) for all $a \in A$ it holds that if $\alpha(a) \neq \alpha'(a) \Rightarrow \alpha'(a) \neq \alpha(a')$ for all $a' \in A$ (target vertex must be empty);

(iii) and for all $a, a' \in A$ it holds that if $a \neq a' \Rightarrow \alpha'(a) \neq \alpha'(a')$ (no two agents enter the same target).

Solving the MAPF instance is to find a sequence of configurations $[\alpha_0, \alpha_1, ..., \alpha_\mu]$ such that α_{i+1} results using valid movements from α_i for $i = 1, 2, ..., \mu - 1$, and $\alpha_\mu = \alpha_+$. A *feasible solution* of a solvable MAPF instance can be found in polynomial time [Wilson, 1974, Kornhauser et al., 1984]. Precisely, the worst-case time complexity of most practical algorithms for finding feasible solutions is $O(|V|^3)$ (asymptotic size of the solution is also $O(|V|^3)$) [Luna and Bekris, 2011b].

2.1.1 Cumulative Objectives in MAPF

Two standard objective functions are being used–*makespan* and the *sum-of-costs*. In the *makespan* objective [Surynek, 2017], we need to minimize μ in the solution sequence mentioned above. In our solution, we use solvers that implement the *sum-of-costs* objective [Dresner and Stone, 2008, Sharon et al., 2013, Sharon et al., 2015]:

Definition 2. *The* **Sum-of-costs objective** *is the summation of the number of time steps each agent requires to reach its goal vertex. Denoted $\xi = \sum_{i=1}^{k} \xi(path(a_i))$, where $\xi(path(a_i))$ is an* individual path cost *of agent a_i connecting $\alpha_0(a_i)$ calculated as the number of edge traversals and wait actions.* [4]

Observe that we accumulate the cost of wait actions for agents not yet located in their goal vertices in the sum-of-costs objective. We note that finding an optimal (minimal) solution with respect to the sum-of-costs objective is NP-hard [Ratner and Warmuth, 1986]. Therefore, using search as we do here to solve MAPF optimally is currently the only viable option.

2.2 Real-world Complications

There is a gap between the theoretical MAPF models and deployment in the physical world. This gap consists of the already mentioned assumptions about time and the agents, but also the way how the environment is modeled is problematic. Usually, we model the environment as a tiled grid or undirected graph, but for example, maps in some video games benefit from not being grid-based but instead use polygons [Botea et al., 2013].

Some studies [Li et al., 2019, Andreychuk et al., 2019] considered the geometrical shape and size of the agents, geometry-aware collision detection, and various movement speeds. Also, continuous movements of the agents are used in order to simulate realistic robot movement in a physical environment.

Another assumption of theoretical models is that all agent movements are synchronous, but in reality, there can be many factors that might introduce *desynchronization* into the plan execution. One of these factors is the mentioned variety of actions durations. Because every agent is executing a different sequence of actions, their movements are desynchronized quickly. Fortunately, this factor can be mitigated using a suitable abstract solver, but many factors cannot be anticipated. Some monitoring of the execution is needed when weather, terrain, or other unexpected circumstances might cause desynchronization. The ability of an agent to follow the planned path successfully can be dependant on the environment or its hardware.

The abstract plans should account for unexpected mistakes and delays to prevent unexpected collisions, which can have more significant consequences in the physical world than in the virtual environment. For this, *k-robustness* [Atzmon et al., 2018] can be introduced to the plan. A k-robust plan, besides the classical MAPF plan, requires that no other agent can enter it for the next k time steps after an agent leaves a position. If agents were to move in a train-like formation, there would be empty spaces between them.

2.3 CBS Algorithm

The Conflict-based Search [Sharon et al., 2015] is a two-level optimal MAPF algorithm that decomposes the MAPF problem into several constrained single-agent pathfinding problems that are easier to solve. The algorithm is composed of two searches–high-level search and low-level search.

The *high-level search* is performed on a binary *constraint tree* that is expanding during the search until a valid solution is found. Each node of the constraint tree holds a set of constraints, a found solution, and a cost. All constraints are tuples (a_i, v, t), meaning that the agent a_i cannot be at the vertex v at time step t. Each node inherits the set of constraints from its parent and adds only one extra constraint for a specific agent. The solution in a node is a set of paths

[4] The notation $path(a_i)$ refers to a path in the form of a sequence of vertices and edges connecting $\alpha_0(a_i)$ and $\alpha_+(a_i)$, while ξ assigns the cost to a given path.

Algorithm 1: High-level search of CBS algorithm

Input: MAPF problem instance Σ

$R.constraints \leftarrow \emptyset$;
$R.solution \leftarrow$ paths from low-level search;
$R.cost \leftarrow$ cost($R.solution$);
insert R into $OPEN$;
while $OPEN \neq \emptyset$ **do**
    $N \leftarrow$ node from $OPEN$ with lowest cost;
    validate $N.solution$ until conflict;
    if *$N.solution$ has no conflicts* **then**
        `// it is a valid solution`
        return $N.solution$
    $C \leftarrow$ first conflict (a_i, a_j, v, t) found in $N.solution$;
    foreach *a in $\{a_i, a_j\}$* **do**
        $N' \leftarrow$ new constraint tree node;
        $N'.constraints \leftarrow N.constraints \cup \{(a, v, t)\}$;
        $N'.solution \leftarrow N.solution$;
        update $N'.solution$ for agent a with low-level search;
        if *$N'.solution$ was found* **then**
            $N'.cost \leftarrow$ score($N'.solution$);
            insert N' into $OPEN$;

for all agents found by the low-level search. Each of the paths is restricted by the constraints for the given agent. The cost of the node is the cost of the found solution. In Algorithm 1, the pseudocode of the high-level search of CBS is shown. At the beginning of the search, the root of the constraint tree is initialized. The set of constraints in the root node is empty, and the solution is a set of shortest paths for each agent. The tree is searched in a best-first manner, meaning that the lowest-cost node from the open nodes is processed and expanded in each iteration. A solution of the currently processed node is checked for conflicts between agents in their paths. If there is no conflict, the solution is valid, and these paths are returned. If a conflict is found, two new constraints are added to the constraint tree for this conflict. The conflict is a tuple (a_i, a_j, v, t), meaning that both agents a_i and a_j occupy vertex v at time step t. The node is split into two child nodes, each introducing a new constraint for one of the conflicted agents and holding an updated solution. For example, for agent a_i, a new constraint (a_i, v, t) is added. Then the path of the agent a_i from the previous solution is replanned with the low-level search that uses the new set of constraints. If the low-level search founds a valid path for this agent, the node is added to the set of open nodes.

Figure 2: Ozobot Evo robot (photo from [Evollve, Inc., 2020a])

The *low-level search* performs a simple single-agent pathfinding search for a given agent while making sure the solution does not break any constraints concerning the agent. In this low-level of CBS, any optimal single-agent pathfinding algorithm can be used. The constraints that the algorithm needs to handle ensure that none of the previously-detected conflicts in the high-level search is repeated in the new path.

3 Robotic Agent: Ozobot Evo

In our deployment of MAPF solutions, we use a swarm of small mobile robots–Ozobot Evo [Evollve, Inc., 2020b]. An image of the Ozobot Evo robot is in Figure 2. It is equipped with a considerable amount of sensors and other hardware, as can be seen in a visual breakdown of the robot in Figures 3 and 4.

The primary capability of Ozobot Evo is to follow lines, which is also its default reflex behavior. This behavior can also be altered using Color Codes or OzoBlockly. *Color Codes* are instruction markers that can be read and executed by Ozobot, and *OzoBlockly* is a visual code editor where the user can control almost all of the robot's hardware. It is more affordable to build a swarm from Ozobot Evo robots compared to other conventional mobile robots used in research. However, Ozobot is more limited in terms of functionality and hardware.

3.1 Hardware and Movement

Ozobot can move around using its *motor and wheels*. By turning the wheels separately at different speeds, it can turn and follow curved trajectories. Under the base of the Ozobot are several line sensors and an optical color sensor. The purpose of the sensors is to detect lines and surface color. The *color sensor* can distinguish eight different colors, and Ozobot is highly dependant on it because it allows the robot to read

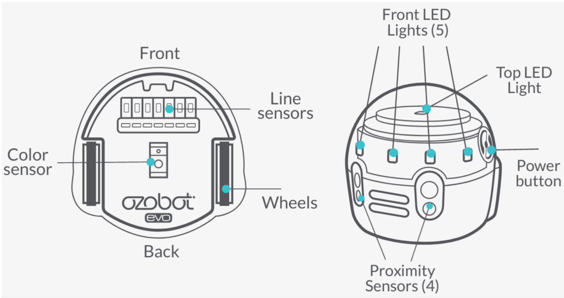


Figure 3: Sensor layout of Ozobot Evo (photo from [Evollve, Inc., 2020c])

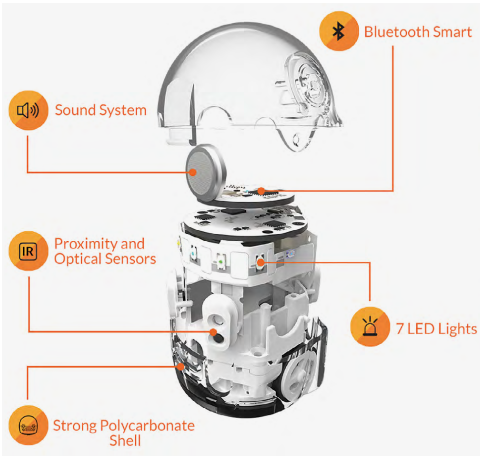


Figure 4: Breakdown of Ozobot Evo (photo from [Evollve, Inc., 2020c])

Color Codes. It is also used to load programs into the Ozobot's memory.

The essential reflex functionality of Ozobot we used in our deployment is line following. By default, Ozobot follows lines at a speed of 30 mm/s. The robot can detect line intersections, where it chooses one of the possible directions at random. It is important to know that Ozobot does not register a 90-degree turn as an intersection. Ozobot can follow lines either on a paper or on display, and it can also transfer between different surfaces. If the robot loses the line it is following, it stops its motion. While following lines, Ozobot will also read and execute *Color Codes* if found.

The hardware of the robot is fairly limited, and different line properties, like line thickness or angle of turns, need to be set correctly for accurate detection and following. It is also recommended to calibrate Ozobot before every use to ensure the correct functionality of its optical sensors.

4 Deployment Strategies

The previous solution of discrete MAPF solution deployment on physical robots from [Barták et al., 2018] worked well for direct comparison of MAPF models. In their deployment, the authors translated found solutions into the Ozobot's movement primitives that can be loaded into the robot as an OzoBlockly program. Rotation actions had to be included in the abstract model, and it was ensured that all actions have the same duration. Each Ozobot with its individual path was then placed on a grid map printed out on a paper, where the plan execution was performed.

Because of how this strategy utilizes Ozobots, there are several drawbacks that could be solved using a different deployment strategy:

- It is unattainable to start the plan execution synchronously for a large number of robots since the execution is started manually.
- Robots need to be individually reprogrammed before deployment on a new problem instance.
- Abstract models and MAPF solvers need to be modified in order to use them for this deployment.

In our deployment strategy, we use Ozobots as purely reflex-based agents with a *fixed behavior*. The agents navigate in an *environment that can output information* for them, affecting their behavior. In our case, the environment is a surface of a display on which the Ozobots can move. Their paths are displayed underneath them as control lines the robots can follow. The plans are obtained from a *discrete centralized MAPF solver* and then processed for the displaying on the screen.

4.1 Expected Problems

Even if the MAPF solver finds a valid solution, *collisions* can still occur if the environment is modeled incorrectly. Sufficient space between positions needs to be ensured so the robots can move around each other without any contact.

The biggest issue is the *desynchronization* of the plan execution. This problem can be caused, for example, by the limited hardware of the robots. Since the actions of robots in our deployment do not have the same duration, the path execution will desynchronize very quickly. In order to perform a successful plan execution, we need to mitigate the desynchronization problem and have the agents to self-correct their position on their individual paths.

5 Hardware Desynchronization

To test if the Ozobot's hardware is prone to cause desynchronization by itself, we implemented similar deployment as in [Barták et al., 2018]. Maps representing different problem instances are printed out on paper on which Ozobots can move. We implemented a modified version of the CBS solver to support robot rotation as actions in planned paths. The individual paths of the found solutions are translated into the following movement primitives:

- Follow the line to the next intersection (forward movement);
- rotate 90 degrees left;
- rotate 90 degrees right; and
- wait.

The sequences of these actions are loaded into the Ozobots as an OzoBlockly program and then executed on the printed map.

To isolate the desynchronization caused by hardware limitation, we had to assure that each action has the same duration. The configuration used is in Table 1. Each action was configured to take precisely 1.86 seconds. For the move and rotate actions, additional wait time needed to be added to assure perfect timing.

Table 1: Ozobot action configuration

Action	Speed [mm/s]	Wait time [s]	Duration [s]
move	35	0.05	1.86
rotate	15	0.85	1.86
wait	0	1.86	1.86

5.1 Evaluation

This deployment was tested on five different maps, where the execution time was compared to the computed reference time of the plan. An example of a map called *turtle* is in Figure 5.

Table 2: Average desynchronization per action and map in milliseconds

Map/Action	Move	Rotate	Wait
grid	2.1	9.5	0.0
tunnel	9.0	9.5	16.8
race	6.0	2.0	11.0
roundtunnel	5.5	11.0	0.0
turtle	7.4	5.1	1.7

On each map, we measured the average desynchronization for each action compared to the reference action duration. These time differences in milliseconds can be found in Table 2. The time differences of each action compared to the reference time

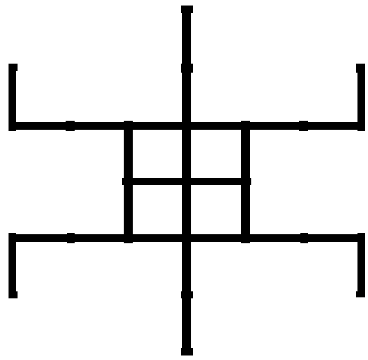


Figure 5: An example of a map used for the desynchronization experiment

1.86 seconds were from interval $(-154, 256)$ milliseconds.

Overall, the desynchronization was notable, but not large enough to cause accidental collisions between agents. No plan was executed with a time difference of more than 408 milliseconds from the reference plan duration. In more complicated plans, this inconsistency of action duration could pose a problem for the execution.

6 Deployment Prototype

We have implemented a prototype of the reflex-based deployment strategy, as explained in Section 4 in Python. In this section, we go through some of the aspects of the deployment in more detail. We primarily concentrate on the aspect of desynchronization and its mitigation using the reflexive behavior of the agents.

The application takes a map file that contains the MAPF problem instance we want to solve and execute on the hardware. The solution is found by an already existing and unmodified MAPF solver, and the plan is processed. Both the map and paths are then displayed on a screen on which the Ozobots are located. The reflexive behavior of the robots had to be modified.

6.1 Environment

For our prototype, we chose to use *grid-based maps*, which can be easily represented as grids of tiles on the screen. The abstract representation of the graph, with which the MAPF solver operates, is an undirected graph. The abstract representation with the solution is then converted to a drawable map that can be displayed in the physical environment–the surface of the screen.

An example of a map is shown in Figure 6. If there is no edge between two neighboring vertices in

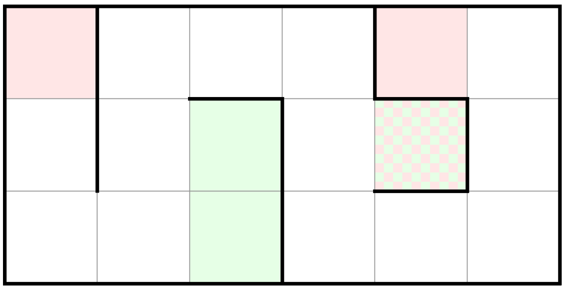


Figure 6: An example of a map displayed on the screen before the simulation

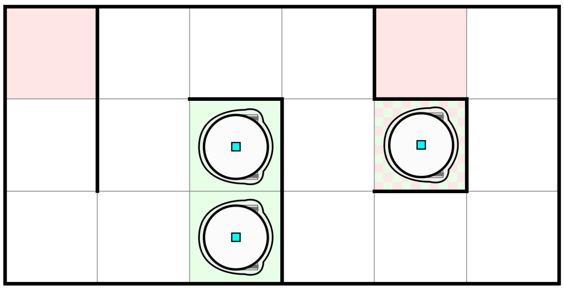


Figure 7: The map example with Ozobots ready to execute paths

the original graph, a *wall* is displayed on the map between the corresponding tiles. The walls are also displayed all around the map to indicate the perimeter. With green and red color, we mark tiles that represent a *start* or *goal* position of the agents. If there is a start and also a goal position on a single tile, the tile is filled with both colors using a checker pattern. Note that the colors need to have very *low opacity*, so as the Ozobots do not register them as following lines. At the beginning of the execution, Ozobots are placed on the green tiles, as shown in Figure 7. In the end, they should stand on the red tiles. During the execution, the planned *paths* are displayed underneath the robots.

6.2 MAPF Solver

The prototype uses an already existing program that implements the SMT-CBS algorithm [Surynek, 2019], which combines the SAT-based solving principle and the CBS algorithm. All algorithms in this program are implemented under the *sum-of-costs* objective function.

6.3 Path Animation

To perform the path execution with Ozobots, we need to transform the discrete solution into continuous paths and display them on the map. When the

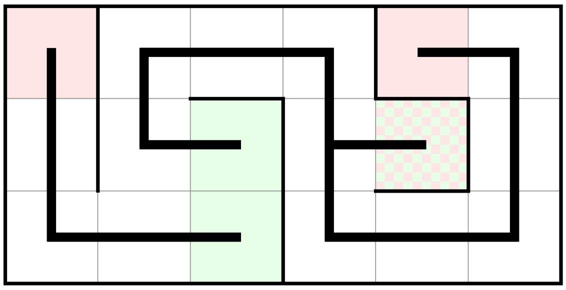


Figure 8: Full agent paths displayed on the map

plan is displayed, Ozobots should be able to execute their paths without any manual interference.

The simplest solution for the path outputting would be to display the whole plan at once, as shown in Figure 8. Unfortunately, this method introduces a problem for Ozobots. When paths of at least two agents cross, an intersection is created in the displayed following lines, where Ozobots choose their direction randomly. Therefore, each robot would need to memorize a sequence of directions it needs to choose at the intersections on its path. Ozobots would also be unable to wait in a specific position.

These problems can be solved by animating the paths. At every moment, only a small path segment underneath each robot is displayed. By moving the path segment, Ozobot should always have a line to follow. However, when following the paths, Ozobot does not have a constant speed because of turns. Therefore the plan execution of the swarm desynchronizes, and we cannot be sure where the robots are located at a given moment. The main issue is that if a robot moves too slow, it will lose the path segment, and if it moves too fast, it can lose it at a turn.

6.3.1 Reflexive Synchronization

We use reflexive behavior to mitigate the desynchronization of the plan execution. The idea is to have the robots change their speed of movement reflexively depending on their position on the animated path segment. This would result in a positional correction of the robots on their paths. When the robot falls behind the path segment, it needs to increase its following speed to keep up with the following line. On the other hand, when Ozobot gets close to the head of the path segment, speed needs to be decreased.

Because the robot needs to know when and how to change its movement speed, the environment outputs need to convey this information. This could be achieved by displaying colored path segments and having the robots change their movement speed based on the color. Ideally, the color of the path segment would gradually change along the line's length. For

(a) Ideal gradient colored path

(b) Path segment divided into colored parts

Figure 9: Two versions of colored path segments

example, from blue color at the front to red color at the end, as shown in Figure 9(a). The robot, moving on the following line, would continually read the line color underneath its optical color sensor and gradually change its movement speed. The speed would be increased towards the red color and decreased towards the blue color, forcing the robot to stay in the middle of the path segment.

However, this ideal path segment representation and agent behavior are not achievable due to the Ozobot's limitations. Ozobot cannot read the exact values of color channels but instead recognizes eight different colors. Therefore, a color gradient could not be fully exploited, and the path segment had to be divided into a few colored parts, as shown in Figure 9(b).

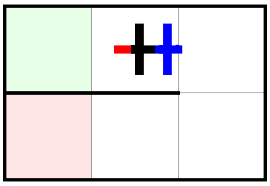
6.3.2 Colored Paths

Another drawback is that Ozobot cannot read from its optical sensors while executing a line following command. To solve this problem, artificial intersections have been added to the paths to interrupt the line-following command in order to perform color readings. Each of the three colors corresponds to different movement speed. The final version of the colored paths is shown in Figure 10. Turns in paths are drawn as curves to make the turning of the robots smooth. If the agent has to stop at a specific position, the path segment stops its animation at the position. In some scenarios, the robot is required to make a U-turn. For this functionality, a special Color Code supported by the Ozobot is displayed on the screen. The robot can read the code and perform the turn.

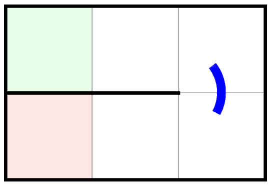
An illustration of Ozobots navigating on the path segments is shown in Figure 11.

6.4 Reflexive Behavior

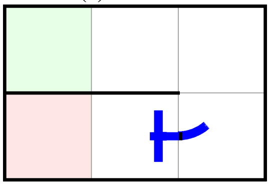
The reflexive behavior of the Ozobot agents is written as an OzoBlockly program and loaded to all robots in the swarm. The behavior needs to follow the path segments, read line colors, and adapt the movement speed accordingly. The program can be found in Algorithm 2. The main loop runs until the program is manually terminated. As shown on line 7 of the code, the robot moves on the path segments between the artificial intersections until it loses the following line. When an intersection or a line end is encountered, the line-following speed is updated on line 2. Because the Ozobot naturally wants to choose a random direction at any intersection, line 4 makes it always go straight. However, if the movement was interrupted and there is no line under the robot, line 6 stops it from moving.



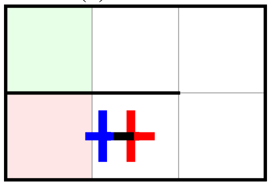
(a) $t = 2.5s$



(b) $t = 4.5s$



(c) $t = 6.0s$



(d) $t = 7.0s$

Figure 10: Colored path segments displayed in the map after t seconds from the start of the execution

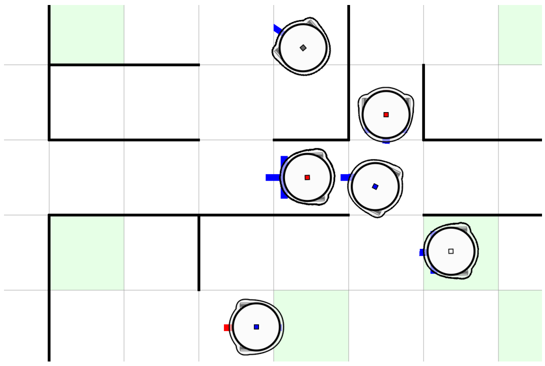


Figure 11: Illustration of Ozobots following colored path segments on a map

Algorithm 2: Ozobot behavior program

```
1 while true do
2     set line-following speed:
        getSpeedFromLineColor() mm/s;
3     if there is way straight then
4         pick direction: straight;
5     else
6         stop motors;
7     follow line to next intersection or line end;
```

The function `getSpeedFromLineColor` from line 2 is shown in Algorithm 3. First, the function reads

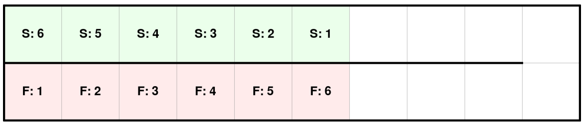


Figure 12: Experiment map: The snake

the surface color from the Ozobot's optical color sensor on line 2. On lines 3–10, the speed is chosen according to the color, and on line 11, it is returned. The speeds on each of the segments were chosen based on the path segment animation speed.

Algorithm 3: Function reading line color and returning speed

```
1  Function getSpeedFromLineColor()
2      color ← get surface color;
3      if color = surface color red then
4          speed ← 37;
5      else if color = surface color black then
6          speed ← 30;
7      else if color = surface color blue then
8          speed ← 23;
9      else
10         speed ← 21;
11     return speed
```

7 Experimental Evaluation

The prototype was experimentally evaluated on various scenarios where the focus was on the success of execution. Each of the problem instances, represented by a map, was solved with both the move-to-unoccupied variant (denoted *m2u*) and the *standard* MAPF solver[5].

7.1 Maps

For the experiments, four maps were used. Some of the maps aim to test a specific feature, others provide a balanced scenario for the execution. All of the maps are listed in Table 3, and the previews of these maps are shown in this section. For each map, its width, height, and number of agents are provided in the table.

7.2 Results

Every plan was executed 32 times with the implemented prototype. The execution is marked as *successful* if all Ozobots reach their goal positions. If at least one loses the following line and does not reach the goal, the execution is marked as a *failure*. The plans are listed in Table 4, where also the results of the experiments are summarized. During the testing, two main reasons for execution failure were recorded. The occurrence of these failures was counted and is presented in the table of results.

The first reason for the failure of the execution is robot *collision*. Most of the time, slight bumps did not cause any significant issues. Sometimes, however, robots collide in a way where they block each other and cannot continue the plan execution. This problem does not occur very often and is non-existent in the move-to-unoccupied plans.

The second reason is an *incorrect detection* (ID) of the sensors. This problem has occurred in various situations. The most noticeable was incorrect execution of the *Color Code*, where the robot did not execute the *U-turn* command, or it executed it twice. In both scenarios, the robot faced the wrong direction and could not continue the plan execution. Sometimes, Ozobot even failed to detect an intersection and update its speed. The occurrence of this mistake resulted in execution failure if it happened before a turn, where the robot needs to slow down. When

[5]For some maps, these two plans are identical, and only one of them is experimented on.

Table 3: Maps created for experiments

Map name	Width	Height	Agents	Image of the map
snake	10	2	6	In Figure 12
rotation	5	5	4	In Figure 13
swap	8	3	6	-
ordering	5	3	3	-

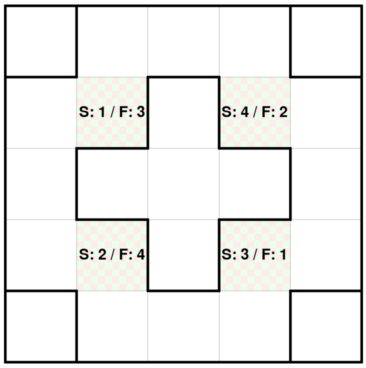


Figure 13: Experiment map: The rotation

Table 4: Results of the experiments

Plan name	Success	Fail	Collision	ID
snake	32	0	0	0
snake_m2u	32	0	0	0
rotation	29	3	0	3
swap	30	2	0	2
swap_m2u	30	2	1	1
ordering	30	2	1	1
ordering_m2u	24	8	0	8

the robot was required to perform a wait action on a turn, sometimes it oriented itself incorrectly. This resulted in a situation where it could not follow the path segment that reappeared underneath it. On rare occasions, Ozobot was unable to follow the path correctly after a turn.

7.3 Summary of Results

Overall, these experiments demonstrated the ability of this deployment strategy to be used for the execution of MAPF solutions that are even constructed on top of the classical discrete MAPF abstraction. The simulation with physical robots also shown that this ability to perform the plan execution correctly is highly dependent on the physical agents and their ability to read and respond to the environment outputs. As for the Ozobots, their main weakness is the variable accuracy of optical sensors with different light conditions. A reflex-based active correction of desynchronization showed to be successful in keeping the plan execution synchronized. Since the experiments were successfully performed on such limited hardware, it indicates that better results could be achieved with more sophisticated robotic agents.

8 Conclusion

This work has described a new strategy of deploying discrete MAPF solutions on a swarm of reflex-based physical robots. A swarm of Ozobot Evo robots has been used for the prototype application. The prototype showed that using the reflexive behavior of the agents can be used to implement active correction of desynchronization that can occur during the plan execution. It has also been confirmed that discrete MAPF solutions can be deployed on reflex-based robots that move continuously using environment outputs.

Experiments performed on the system identified several problems that need to be overcome to execute the plan execution successfully. Most of them are dependent on the capabilities of robots being used. Using reflex control of robots through path animation on the surface of the screen makes this strategy capable of functionality extensions.

This deployment strategy can also be used for MAPF demonstrations in research or academics. Some real-world applications like intelligent evacuation systems and indoor transporter navigation in warehouses also could benefit from this approach.

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