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Proposal of Primitive Swarm Robot Navigation Strategy for Adaptively Traversing Unspecified Environments

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Abstract: This study proposes a navigation strategy for swarm robots to adaptively traverse an unspecified environment. The unspecified environment is an environment that changes unpredictably from moment to moment according to the laws of physics, such as a disaster site or the moon's surface. Such environments are essentially different from previously proposed unknown environments, and cannot in principle be accurately modeled in real-time, i.e., they cannot be known. In contrast, we accept that robots get stuck in an unspecified environment, and we seek to solve this problem through the cooperative navigation of multiple simple swarm robots. In our previous work, we proposed the "BYpassing COmpanions Method for Swarm robot navigation (BYCOMS)" in which each robot moves toward the goal while avoiding surrounding robots. The effectiveness of this navigation method is demonstrated in an environment where there are static areas where robots cannot progress. In this paper, we report that the proposed method is adaptive to changes in the environment where the robot's impassable zone changes dynamically and unpredictably.

Keywords: Swarm robot, navigation, unspecified environment, open design

1. INTRODUCTION

Robots that work in harsh environments such as landslide sites and on the moon's surface need to traverse these environments without getting stuck. The previous research adopts real-time environment map formation using cameras and LiDAR, called SLAM, as well as self-position estimation and safe path generation to avoid obstacles based on the map[1, 2]. Another approach is the Sim to Real approach, which models the robot and the rough terrain environment on a physical simulation, acquires robot behaviors through deep reinforcement learning, and verifies the robot's performance on the real machine[3, 4].

However, there are immobile areas in the real environment that cannot be determined from the above vision-based sensor information. Muddy areas with dry surfaces and depressions covered with dead leaves are good examples. Such an impassable zone cannot be known in advance by the robot or even by the robot designer (human). In other words, the real environment is essentially an environment that can only be known by the robot. In addition, since the real environment changes unpredictably from moment to moment according to the laws of physics, it is in principle impossible to accurately model the real environment in real time. We call such the environments as unspecified environments[5].

In this study, we propose a primitive navigation strategy for swarm robots that can adaptively navigate through the unspecified environments. In a previous study, we proposed the BYpassing COmpanions Method for Swarm robot navigation (BYCOMS), a navigation algorithm for traversing unknown environments where robots cannot progress[6]. This method is characterized by a simple behavior rule in which the robot moves toward the goal while avoiding surrounding robots, and the stacked robots indirectly make the unknown environment known to the robot so that the robot can reach the goal. We have demonstrated the effectiveness of the proposed method by numerical analysis of static environment navigation and by testing it on a real robot. This paper confirms that the proposed method can navigate adaptively even when the unpredictable zone changes dynamically and unpredictably during navigation.

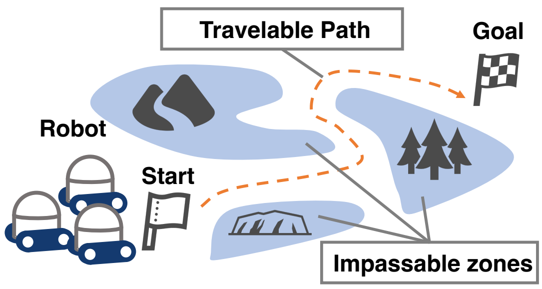


Fig. 1: Problem description of the navigation

2. DESCRIPTION OF THE NAVIGATION PROBLEM

First, an overview of the navigation problem addressed in this paper is shown in Fig. 1. As shown in Fig. 1, there

† Yusuke Tsunoda is the presenter of this paper.

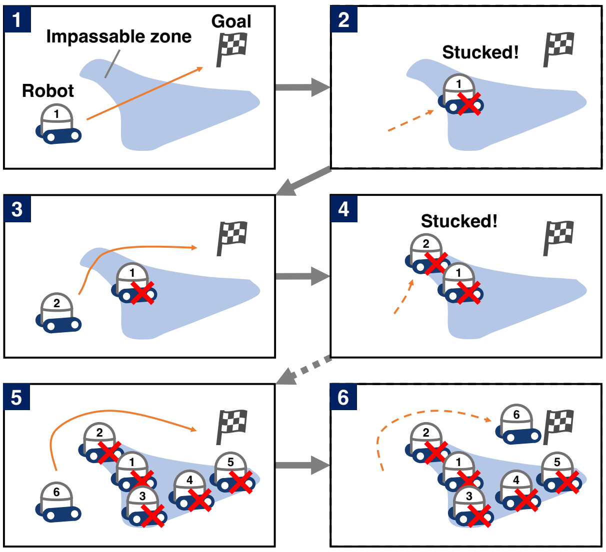


Fig. 2: Proposed method: BYpassing COmpanions Method for Swarm robot navigation (BYCOMS)

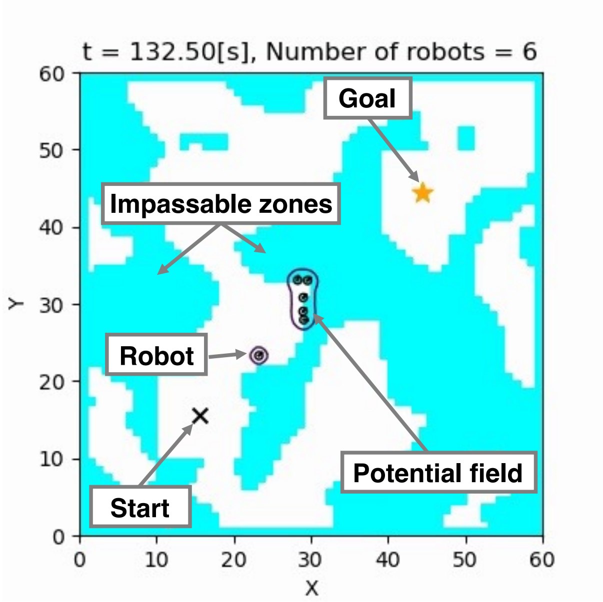


Fig. 3: Simulation environment

exists a closed zone (blue area) in the environment where the robot cannot proceed, and the robot gets stuck (stops) at this boundary. Note that the distribution and shape of this closed zone is unknown and cannot be recognized by the robot or its designer. We assume that there is at least one passable path from the start position to the goal position. The objective is to have at least one of the N mobile robots at the starting point reach the goal under such an environment.

3. BYCOMS: BYPASSING COMPANIONS METHOD FOR SWARM ROBOT NAVIGATION

Next, the navigation algorithm, BYpassing COmpanions Method for Swarm robot navigation (BYCOMS), is described. The details of the algorithm are described in [6]. Fig. 2 shows an overview of BYCOMS. In this method, each robot is assumed to be homogeneous and the number of robots N is sufficiently large. The robots sense the goal direction as global information and their relative positions to surrounding robots as local information. Robots start moving one by one from the start, and get stuck at the boundary of the blue impassable zone. After a robot is stuck, the following robot is launched from the start. The following robot moves toward the goal, avoiding the surrounding robots in the same manner as the starting robot, and gets stuck at the boundary of the impassable zone again. By repeating the above process, the stuck robot implicitly forms a boundary barrier of the impassable zones, and the following robot can indirectly avoid the impassable zones by avoiding the barrier and reach the goal.

4. SIMULATION VERIFICATION

In this section, we verify the effectiveness of the proposed navigation method in an environment where the robot's impassable zones and the goal position change dynamically during navigation by numerical simulation.

4.1. Simulation environment

The simulation environment is shown in Fig. 3. The robot moves in a square 2D planar environment of 60×60. The initial position of the robot is $[15.5, 15.5]^{\mathrm{T}}$ and the goal position is $[44.5, 44.5]^{\mathrm{T}}$. The environment is divided into grids, and the robot has two states for each grid. When the coordinates of the robot enter the blue area of the grid, the robot is considered stuck and stops on the spot. After the moving robot is stuck, a new robot is placed at the start position facing the goal direction and starts moving. The simulation ends when the distance between the robot's center coordinates and the goal is less than the robot radius and the goal is reached, or when 10000 s has elapsed. The time step width of the simulation is 0.1 s and the grid width is 1. For terrain generation, we use perlin noise, which is used to represent random and natural terrain. We use the A* algorithm to determine whether a path exists for the generated terrain that passes only within the robot's mobility range from the start to the goal, and perform navigation on terrain where such a path exists.

4.2. Robot algorithm

Next, we describe the algorithm of the robot. In this study, we implement BYCOMS described in Section 3 in a virtual potential field represented by a physical device with wave-like properties, such as sound or light. The strength of the potential field is set to decay with distance r from the source according to the r^2 law, as in the following equation.

$$g(x, y) = \frac{1}{(x - x_r)^2 + (y - y_r)^2}, \tag{1}$$

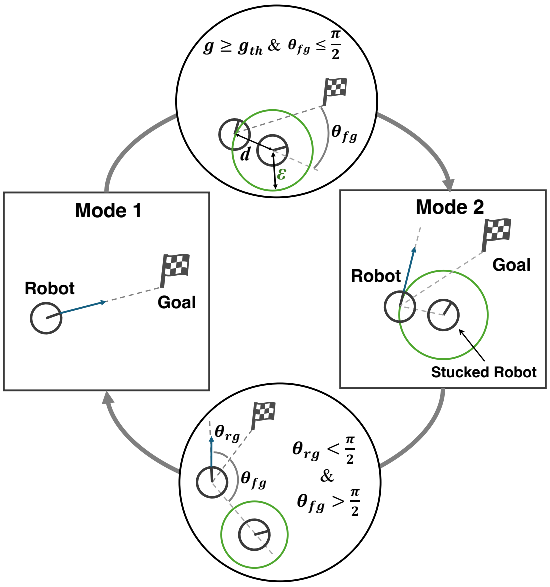


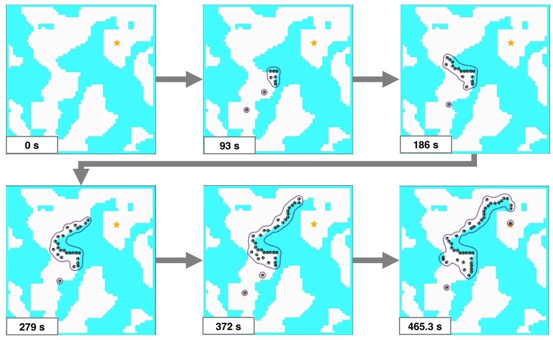
Fig. 4: Robot algorithm

where $[x_r, y_r]^{\mathrm{T}}$ are the coordinates of the robot. Each robot has a certain threshold g_{th} for the strength of this potential, and the distance to surrounding robots is estimated by comparing the potential strength g to be sensed with this threshold. This enables robots to avoid each other.

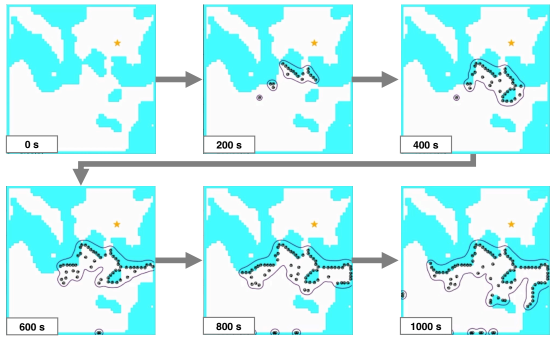
Fig. 4 shows an overview of the robot's action algorithm. While moving, the robot switches between two modes: mode 1 and mode 2. In mode 1, the robot moves straight ahead in the direction of the goal, and in mode 2, the robot moves in a direction perpendicular to the gradient and avoids surrounding robots while keeping the measured potential strength in line with the threshold value g_{th}. The robot chooses the vertical direction of the potential gradient that has a smaller declination with the goal direction. If the difference in angle between the goal direction and the robot's direction of travel is less than $\pi/36$ /rad, the robot will go straight at a speed of 1 /s. Otherwise, the robot turns with a turning speed $\pi/6$ rad/s in the direction where the declination angle becomes smaller. The condition for switching from mode 1 to mode 2 is that the strength of the mobile robot's in-situ potential field g reaches the threshold value g_{th} and the difference angle θ_{fg} between the goal direction and the gradient direction of the potential field becomes $\theta_{fg} \leq \pi/2$ rad. On the other hand, the condition for switching from mode 2 to mode 1 is that the difference angle between the robot direction and the goal direction θ_{rg} is $\theta_{rg} < \pi/2$ rad, and the difference angle between the potential field gradient direction and the goal direction θ_{fg} is $\theta_{fg} > \pi/2$ rad.

4.3. Simulation results for static environment

This section first shows the results of the navigation in the case that the impassable area is static. Fig. 5a shows an example of successful navigation. The threshold for the strength of the robot's potential is $g_{th} = 1$, and the



(a) Snapshots of a successful unknown environment navigation by BYCOMS



(b) Snapshots of an unsuccessful unknown environment navigation by BYCOMS

Fig. 5: Results of unknown environment navigation by BYCOMS

minimum path width is 3. The robot moves from the start position to the goal position and gets stuck at the boundary of the impassable area, and subsequent robots move toward the goal while avoiding surrounding robots. As a result, the robots can reach the goal while avoiding the boundary of the impassable area formed by the stuck robot.

On the other hand, Fig. 5b shows an example of navigation failure. In this simulation, $g_{th} = 1$ and the minimum path width is 2. The cause of this failure is that the path to the goal was blocked by the potential field formed by the robot group itself. From this, in order to achieve navigation, It is important that the relationship between the threshold g_{th} (i.e., the size of the radius of circumference) for the strength of the robot's potential and the size of the minimum path width of the environment. For a mathematical proof of the goal reachability of BYCOMS and the conditions for the radius of circumference of the robot and the minimum path width of the environment for achieving navigation, please refer to [6].

4.4. Simulation results for dynamic environmental changes

This section describes the navigation in environments where impassable areas change dynamically. First, we describe the behavior in response to changes in terrain. In the navigation, we altered the terrain as shown in Fig. 6. The timing of this change was set to the moment when the first robot reached the goal. The results are shown in

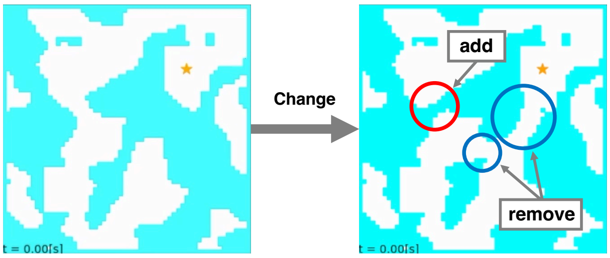
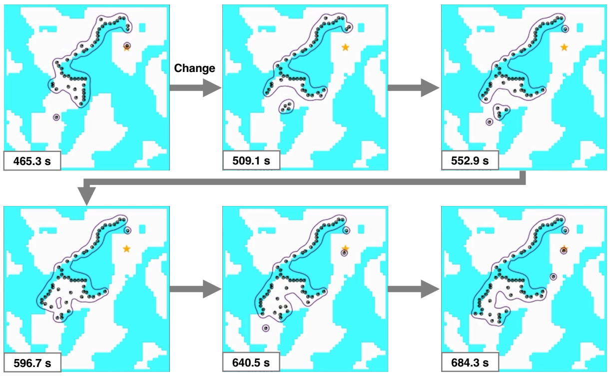
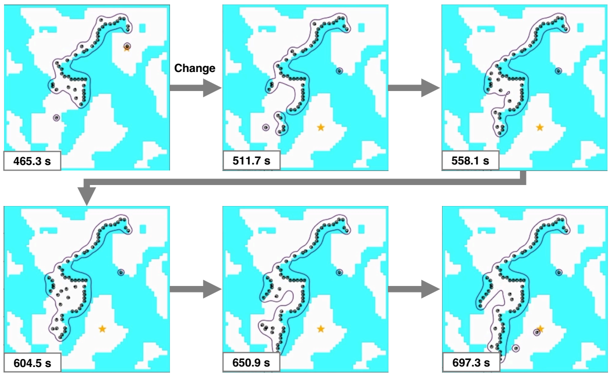


Fig. 6: Topographic change



(a) Snapshots of the navigation in response to topographic change



(b) Snapshots of the navigation in response to goal position change

Fig. 7: Results of the simulations for dynamic environmental changes

Fig. 7a. The previously traversed path was blocked by new obstacles, resulting in the formation of a new potential field in that area, allowing subsequent robots to reach the goal via different routes. We also observed changes in the potential field corresponding to areas where obstacles were removed.

Next, we describe the behavior in response to changes in the goal position. We changed the position off the goal from $[44.5, 44.5]^{\mathrm{T}}$ to $[35.5, 15.5]^{\mathrm{T}}$ during the navigation. The timing of this change was also set to the moment when the first robot reached the original goal. The results are shown in Fig. 7b. In response to the change in the goal position, a new potential field was created, successfully guiding the robots to the new goal. These results demonstrate that the proposed method based on the potential field can adapt to changes in the environment.

5. CONCLUSION

In this study, we proposed a primitive swarm robot navigation strategy for environments with robot impassable zones, and confirmed the effectiveness of the navigation method in environments with dynamically changing impassable zones through numerical simulations. In future work, we plan to mathematically prove the reachability of the proposed method in dynamic environments, and to analyze and evaluate its navigation performance in numerical simulations in response to the way and timing of environmental changes. The current algorithm requires an unrealistic assumption that the number of robots is huge. To solve this problem, we will add a function to determine when a robot is stuck, and investigate a new navigation method that generates an attraction potential field for a moving robot and an avoidance potential field for a stuck robot.

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