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Estimation of obstacle locations using a distribution model of small jumping swarm robots

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***Abstract*— To detect obstacles in narrow spaces, such as under-floor area, herein, we proposed a method that estimates the location of obstacles using a distributed model of swarm robots. First, we constructed a swarm robot model, in which a robot moves by jumping at regular intervals in a field enclosed by walls. We confirmed that, when no obstacles were placed in the field, the spread of the swarm robots followed a Gaussian distribution over a certain period. We then assumed that, even when obstacles were present, the distribution of the robots in the field would follow the Gaussian distribution except in the neighborhood of obstacles. Under this assumption, we proposed a method to clearly estimate the positions of obstacles by taking the difference between the approximated Gaussian distribution based on an average gross distribution of robots over a certain period and the actual average gross distribution of robots in each subdivided area of the field.**

I. INTRODUCTION

In recent years, research on the motion control of swarm robots has focused on exploration and coordinated work using multiple robots [1, 2, 3]. Multiple robots can move autonomously and perform tasks such as traveling to destinations and conducting exploration[4]. Swarm robots excel in robustness, flexibility, and scalability [5], making them suited for collective parallel and cooperative tasks. Specifically, one of them are expected to work in narrow spaces. When small swarm robots explore such spaces, they may have to move over rough terrains. For letting the swarm robots move over the rough terrain, Miyashita et al. proposed swarm robots that jump for locomotion[6]. During the jumping movement, the robots would face the risk of being broken owing to the impact of landing. Therefore, to reduce their weight, a wireless power supply using two coils to supply and receive power was adopted. Because the jumping robot developed by Miyashita et al. moved in random directions when the power is uniformly supplied, it is expected that the distribution of the swarm robots follows a two-dimensional(2-D) Gaussian distribution model in which the number of robots being higher at the center of the swarm and decreasing towards the periphery when the robots are initially placed in a center of field enclosed by walls with no obstacles. We then assumed that the number of robots would follow the 2-D Gaussian distribution even in fields with obstacles, except for local areas where obstacles were set. Under this assumption, we proposed a method to clearly estimate the positions of obstacles by taking the difference between the actual average gross number of robots and 2-D Gaussian distribution approximated from the number of robots over a certain period. In this study, we introduced swarm robots that would move autonomously and showed that estimating the position of obstacles using an approximated distribution model of swarm robots is possible.

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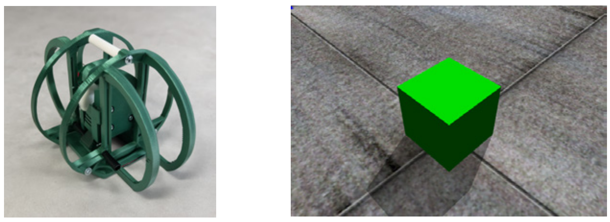
II. SIMULATION SETTINGS

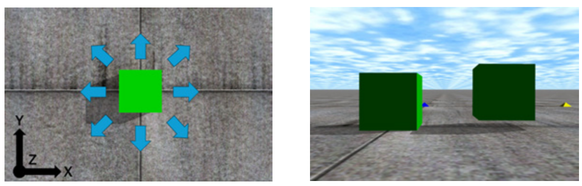
A. Robot setting

In this study, Open Dynamics Engine (ODE) was adopted for the simulation. The robot used in previous research [6] and the one used in our simulation are shown in Figures 1(a) and (b), respectively. The robot used in our simulation weighed 1.0 kg and had a cuboid shape with dimensions of $0.15 \times 0.15 \times 0.15$ m. When the robot jumps, a randomly decided force is added to the X- and Y-axes (+10, -10, or 0 N), while a fixed force +40 N is imposed along the Z-axis. The forces to each axis are added for 20ms out of 1s. Figure 2(a) shows the robot movement direction, and Figure 2(b) shows an image of robot leaping.



(a) Robots used in previous study (b) Robots used in this study

Fig. 1: The robot used in previous studies(a) and the robot used in the simulation in this study(b).

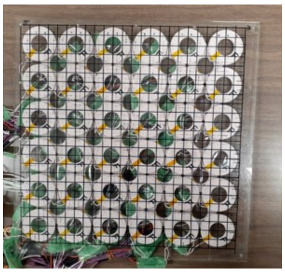


(a) Robot movement direction (b) Demonstration of leaping

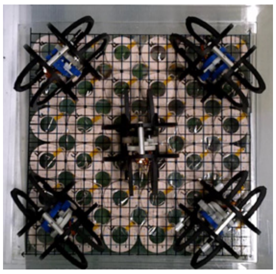
Fig. 2: The robot moves by applying a force in a random direction on the horizontal plane(a) and a constant force in the vertical direction(b).

B. Field setting

Figure 3 shows the field and robots used in [6]. Figure 4 shows the area (light blue), in which the robot moved in this study. The field was restricted by walls. The field was a 10 × 10 m square, and each section of the field was divided into smaller squares of size 1 × 1 m. The origin of the coordinate system was set at the center of the field (see Figure 4(a)). Each of these squares was labeled as follows: The upper left-most area in Figure 4(a) was labeled " Area 1 " and the neighboring right-side area was labeled "Area 2". Following this convention, each square was numbered and the lowest right-most area in Figure 4 was labeled " Area 100 ". The initial position of the 100 robots is shown in Figure 4(b), where each robot was set to jump randomly, as explained above. In the simulation, the average number of robots in each area was recorded over 100 trials for 3600 s.

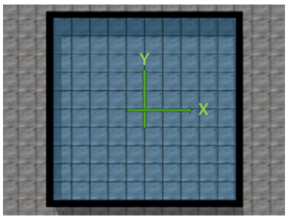


(a) Field

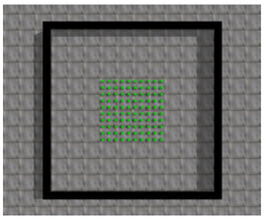


(b) Robot in place

Fig. 3: The field used in previous studies[6] is equipped with power supply coils(a). By placing a robot equipped with a power receiving coil on the field, energy can be supplied to the robot(b).



(a) Field (light-blue colored area)



(b) Robot in place

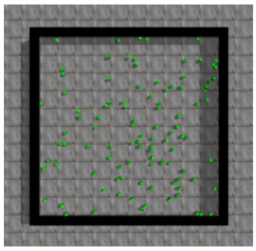
Fig. 4: In this study, we place 100 robots in a field composed of 100 areas and conduct a simulation.

III. SIMULATION EXPERIMENT

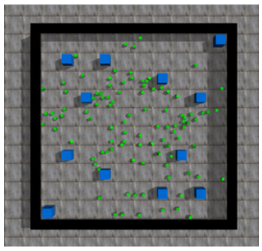
The positions of obstacles in the field were estimated using the following method. The size of the obstacles was 0.25 × 0.25 × 0.25 m, and the obstacles were fixed on the field.

A. Distribution of the robot

Figure 5 show the distribution of robots in the field after a certain period when no obstacles were placed in the field (Figure 5(a)) and when 12 obstacles were placed in the field (Figure 5(b)). Figure 6 shows the number of robots in each area over time, without obstacles (Figure 6(a)) and with the 12 obstacles (Figure 6(b)). Based solely on the results in Figure 6, it is considered difficult to determine the presence or absence of obstacles. Therefore, the average gross number of robots during a certain time period is calculated. Figure 7 shows the average gross number of robots when there were no obstacles in the field for different time periods. Figure 8 shows the average gross number of robots when the 12 obstacles were placed in the field for different time periods.

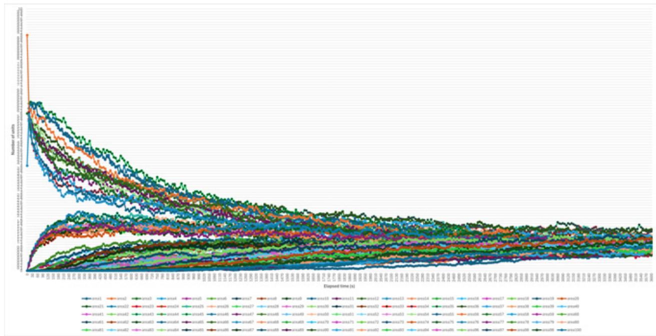


(a) Field without obstacles

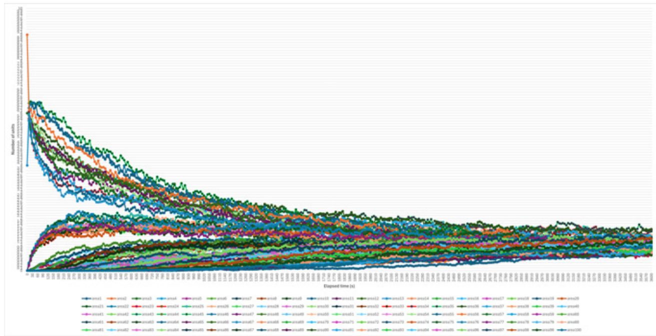


(b) Field with multiple obstacles placed

Fig. 5: The robot moves within a walled field. The robot cannot jump over obstacles placed within the field.



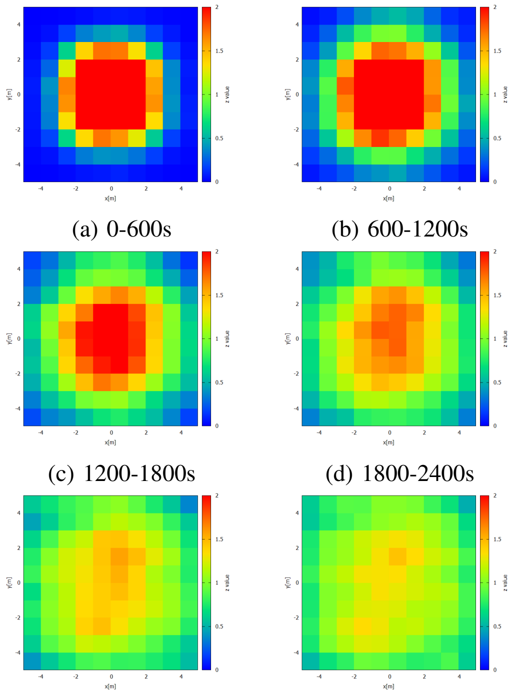
(a) Field without obstacles



(b) Field with obstacles placed

Fig. 6: The robot distribution with respect to time: This result alone makes it difficult to estimate which areas contain obstacles.

As shown in Figures 7 and 8, regardless of the presence or absence of obstacles, the number of robots varied from area to area for some time after the beginning and became uniform after a sufficient period of time. Therefore, to derive a 2-D Gaussian model, in which the number of the robot

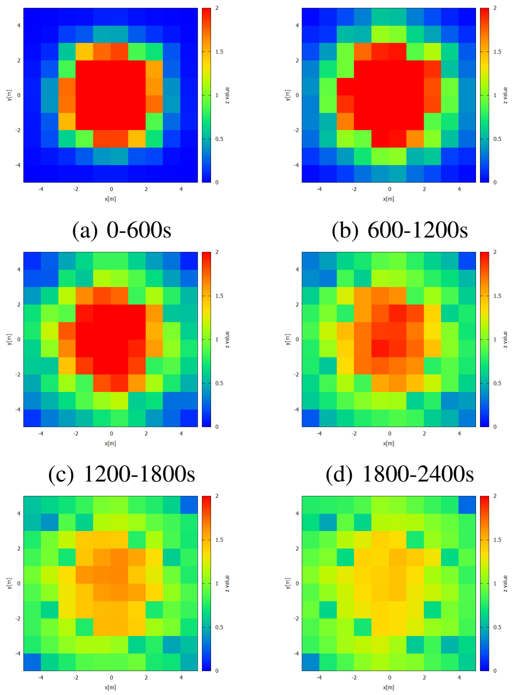


(a) 0-600s (b) 600-1200s

(c) 1200-1800s (d) 1800-2400s

(e) 2400-3000s (f) 3000-3600s

Fig. 7: Average gross number of robots when no obstacles in the field: As time progresses, it can be seen that the robots are dispersing outside the field.



(a) 0-600s (b) 600-1200s

(c) 1200-1800s (d) 1800-2400s

(e) 2400-3000s (f) 3000-3600s

Fig. 8: The average gross numbers of robots when obstacles were placed in the field: Excluding the area where obstacles are placed, it can be confirmed that the distribution of robots is close to a Gaussian distribution.

would be higher at the center of the field, we estimated the distribution of each area based on the average gross number of robots between 3000 and 3600 s, during which time the robots leached to the walls and not uniformly distributed.

B. Estimated Gaussian distribution

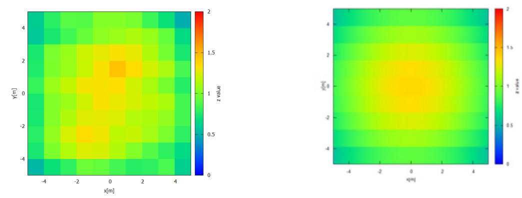
The robot distribution obtained by simulation was fitted to the 2-D Gaussian model using Levenberg–Marquardt (LM) method. The distribution function is as follows:

$$G(x,y) = \frac{N}{2\pi\sigma^2}\exp\left(-\frac{1}{2\sigma^2}\left((\alpha x-\mu_x)^2+(\alpha y-\mu_y)^2\right)\right), \quad (1)$$

where

μ_x and μ_y: Average probability of the robots existence
σ: Standard deviation
N and α: Constants

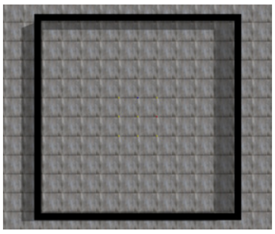
The Equation (1) is a 2-D Gaussian distribution multiplied by a constant N, and the variables x and y are both multiplied by α. We assumed that the average probability of existence in the swarm robot would be at the center of the field (0.0), and μ_x and μ_y were set to 0, respectively. In Equation (1), the center position of each area was substituted for x and y. For example, the center coordinate of Area 1 was $(x,y) = (-4.5, 4.5)$, and the average gross number of robots $G(x,y)$ in each area could be obtained from the fitted parameters σ_x, N, and α, in Equation (1). Figures 9 (a) and (b) show the gross number of robots without the obstacles and the estimated 2-D Gaussian distribution, respectively. Based on these results, we proposed a method to estimate the positions of the obstacles by taking the difference between the 2-D Gaussian model and average gross number of robots in each area.



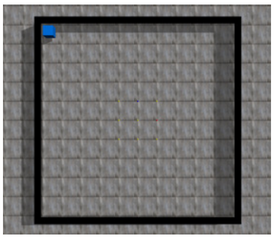
(a) Gross number of robots (b) Estimated 2-D Gaussian distribution

Fig. 9: The distribution of robots obtained from fitting when no obstacles are present: The distribution can be approximated to the model distribution regardless of obstacle presence.

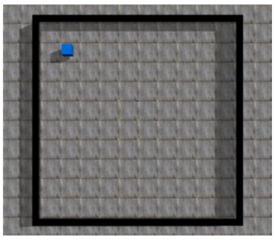
IV. EXPERIMENTAL RESULTS



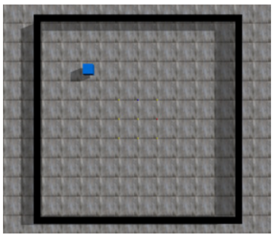
(a) Without obstacles



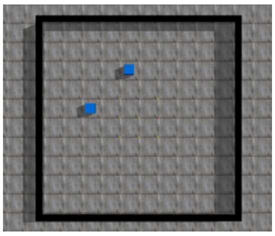
(b) One obstacle [Area1]



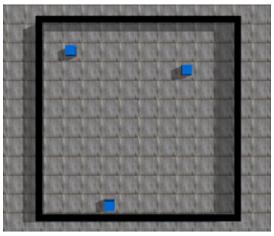
(c) One obstacle [Area12]



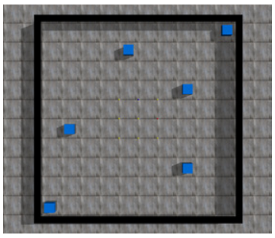
(d) One obstacle [Area23]



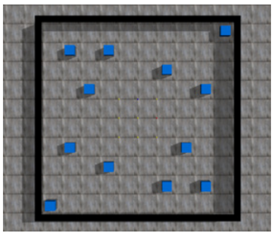
(e) Two obstacles



(f) Three obstacles



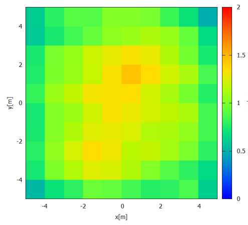
(g) Six obstacles



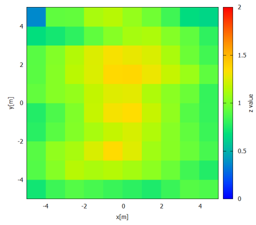
(h) 12 obstacles

Fig. 10: The placement patterns of obstacles in the simulation.

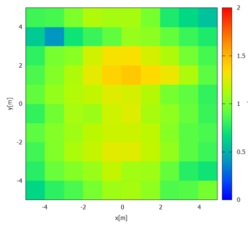
To evaluate the proposed method, we calculated the difference between the model distribution (Equation (1)) in each area and robot distribution recorded in the simulation when the number of obstacles was 0, 1, 2, 3, 6, and 12. Figure 10 shows the pattern of obstacles placed in the field. Figure 11 shows the robot distribution recorded in the simulation corresponding to each pattern, and Figure 12 shows the results of the difference between the 2-D Gaussian model and robot distribution. Figures 11(a)–(f) demonstrate that the gross number of robots decreased as a function of the distance from the center of the field regardless of the number of obstacles. This implies that the distribution of the robots followed a 2-D Gaussian distribution even with the obstacles being present.



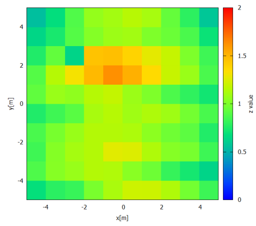
(a) Without obstacles



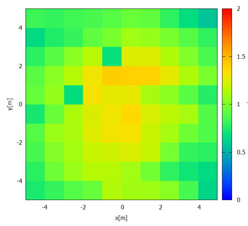
(b) One obstacle [Area1]



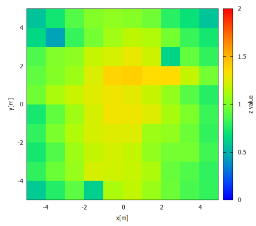
(c) One obstacle [Area12]



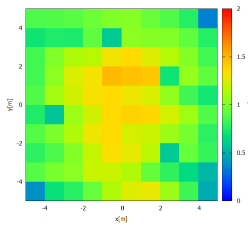
(d) One obstacle [Area23]



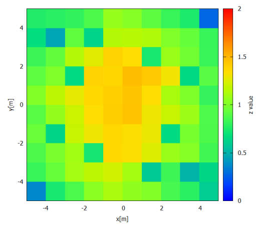
(e) Two obstacles



(f) Three obstacles



(g) Six obstacles

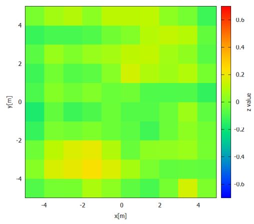


(h) 12 obstacles

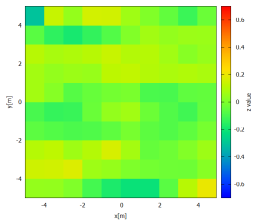
Fig. 11: The average gross number of robots in each area during the simulation: This result alone makes it difficult to accurately estimate the position of obstacles.

Fewer robots were present in areas with obstacles than in other areas. However, in some areas without the obstacles, the gross number of robots recorded was almost the same as that in areas with obstacles, and estimating the locations of the obstacles using this distribution was difficult. On the other hand, Figures 12(a)–(f) show that the difference between the Gaussian and actual robot distributions was almost uniform in areas without the obstacles, whereas this difference became more specific in areas with the obstacles. Negative values in the areas imply that the obstacles were placed in the area.

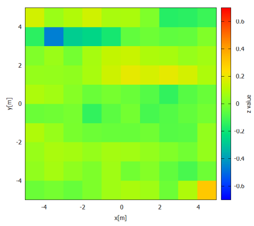
From these results, it was concluded that the positions of the obstacles could be clearly specified by taking the difference between the 2-D Gaussian model and the average gross number of robots.



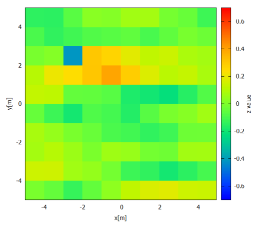
(a) Without obstacles



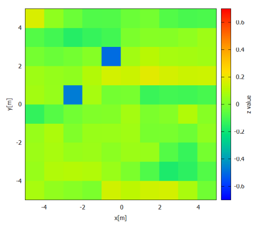
(b) One obstacle [Area1]



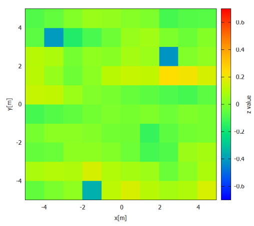
(c) One obstacle [Area12]



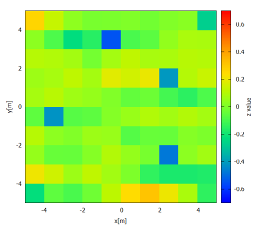
(d) One obstacle [Area23]



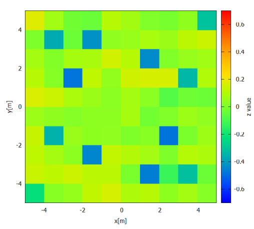
(e) Two obstacles



(f) Three obstacles



(g) Six obstacles



(h) 12 obstacles

Fig. 12: The difference between the model distribution and the robot distribution recorded through simulation (Figure 11). This result indicates that the position of obstacles can be estimated more accurately.

Table 1 that corresponds to Figures 10 to 12 lists the areas where the obstacles were set and the differences between the Gaussian and the actual distributions of robots. When obstacles were placed in areas close to the center of the field, the values were specifically small in the range of approximately -0.5 to -0.3, and estimating the position of the obstacles was possible. On the other hand, as shown in Table 1 and Figure 12, when obstacles were placed in areas far from the center of the field (such as Area 10 and Area 91), the absolute value of the difference tended to be relatively small. This is because fewer robots were present in this area in the Gaussian distribution, and the difference was smaller. This indicates that estimating the positions when obstacles were located far from the center of the field may be difficult. In Table 1, the absolute value of Area 12 for example, was decreased when the number of obstacles was increased (1 obstacle: − 0.47; 3 obstacles: − 0.41; 5 obstacles: − 0.38). This suggests that an increase in the number of obstacles may reduce the estimation accuracy. In this experiment, the size of the obstacle was 0.5 m × 0.5 m × 0.5 m. We also had the experiments in which the size of the obstacle was less than 0.5 m × 0.5 m × 0.5 m, and we found that the accuracy of the estimated position of the obstacle got lower. We expect that the accuracy will be higher by reducing the size of the area.

TABLE I: Differences in areas where obstacles were placed

Units	Obstacle location	Difference
1	Area 1	-0.31
1	Area 12	-0.47
1	Area 23	-0.42
2	Areas 25, 43	-0.50, -0.47
3	Areas 12, 28, 94	-0.41, -0.42, -0.36
6	Areas 10, 15, 38, 52, 78, 91	-0.28, -0.55, -0.42, -0.43, -0.48, -0.23
12	Areas 10, 12, 14, 27, 33, 39, 62, 68, 74, 87, 89, 91	-0.32, -0.37, -0.43, -0.44, -0.49, -0.34, -0.36, -0.49, -0.46, -0.47, -0.32, -0.22

V. CONCLUSIONS

In this study, we proposed a method to estimate the positions of obstacles in a field using a distributed model of swarm robots. In the simulation, we recorded changes in the robot distribution when no obstacles were set. When some obstacles were set, we considered the difference between the Gaussian model and robot distributions. Consequently, in areas with obstacles, the absolute value of the difference was larger than that in other areas without obstacles. Based on these results, we conclude that estimating the positions of obstacles placed in a field by using swarm robots that move randomly without communication, between them and a central computer would be feasible.

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