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Discrete analysis in obstacle clustering by heterogeneous robots

Yuichiro SUEOKA†‡, Takuto KITA†, Masato ISHIKAWA†,
Yasuhiro SUGIMOTO† and Koichi OSUKA†

†Department of Mechanical Engineering, Osaka University
2-1, Yamada-oka, Suita, Osaka, 565-0871 Japan
‡Research Fellow of Japan Society for the Promotion of Science
5-3-1, Koji-machi, Chiyoda-ku, Tokyo, 102-0083 Japan
Email: s.yuichiro@dsc.mech.eng.osaka-u.ac.jp

Abstract—In this paper, we discuss some phenomena of obstacle clustering by distributed autonomous robots, in the light of space-discretization (or cellular automata) approach. This work was motivated by Swiss Robots, which collect scattered obstacles into some clusters without any global information nor intelligent concentrated controller. Then we define fundamental event rules in this cellular world, and introduce two types of local rules for robot action: one is the Push & Turn rule, which can collect obstacles, the other is Pull & Turn rule, which can scatter obstacles. By defining a indix (ratio of immobile obstacles), we investigate the dynamic equilibrium of obstacle clustering by heterogeneous agents.

1. Introduction

It's always seemed like a big mystery: how nature, seemingly so effortlessly, manages to produce so much that seems to us so complex even if individual element or agent is very simple. For example, living things like ants or bees, which have very tiny brains and memories, often construct very big complicated nest [1][2]. In the field of robotics, Deneubourg proposed the robots which can only perceive objects just in front of them and carry them from a simple local rule, but can distinguish between objects of two or more types [3]. On the other hand, utilizing the morphology of the body, Pfeifer proposed Swiss Robots, which can collect obstacles into some clusters without any global information nor intelligent concentrated controller [4][5].

In this research, we have focused on the pattern generations generated by static agents and mobile agents. Then, we propose to assume that everything happens on a discretized state space (hexagonal cellular space). This cellular automata approach was proposed to investigate complex systems (*e.g. self-organization*) [6][7].

Then we define fundamental event rules in this cellular world, and introduce two types of local rules for robot action: one is the *Push* & *Turn* rule which collects scattered obstacles into some clusters, and the other is *Pull* & *Turn* rule which scatters collected obstacles. In this paper, we take closer look at clustering behaviors in heterogeneous system with two different types of robots.

This paper is organized as follows. Section 2 prepares basic properties hold on hexagonal cellular space, and introduces two types of local rules for robot action. Section 3 makes basic simulations of each robot, and introduces a evaluation index. Section 4 analyzes the dynamic equilibrium in heterogeneous system.

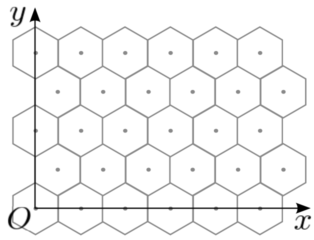


Figure 1: Coordinate settings in the hexagonal cellular space.

2. Rules of the discrete world

In this section, we consider a discrete version of the pattern generation. We first propose to assume that everything happens on a discretized state space. Then we define fundamental event rules in this cellular world, and introduce two types of local rules for robot action: one is the *Push* & *Turn* rule which collects scattered obstacles into some clusters, and the other is *Pull* & *Turn* rule which scatters clustered obstacles.

2.1. Spatial discretization

Suppose a tessellation of the 2-dimensional Euclidean space $\mathbb{R}^2$ with *unit equilateral hexagons*, as shown in Figure 1. In order to deal with limited size of the field, we have to impose some assumption on boundary. In this paper, we suppose that the field has *Torus*-like topology; namely, the right edge of the field is identified with the left one, and the top one is identified with the bottom one (See Figure 2). Thus the coordinate space $\mathbb{Z}$ is replaced by $\mathbb{Z}_N^2$ if the field contains N by N cells.

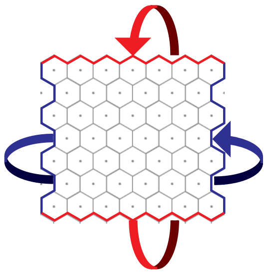
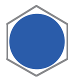


Figure 2: Periodic boundaray condition

(a) A robot



(b) An obstacle

Figure 3: Objects

2.2. Fundamental rules

The world in concern consists of the hexagonal cellular space, robots and obstacles. A *robot* occupies a cell (Figure 3(a)), and has its own state in $\mathbb{Z}_N^2 \times \mathbb{Z}_6$. An *obstacle* also occupies a cell (Figure 3(b)). An obstacle does not have its orientation, so its state is in $\mathbb{Z}_N^2$. Multiple agents can never occupy a single cell; i.e., each cell is empty, or contains either a robot or an obstacle. State of the world is collection of states of all the robots and obstacles.

State of the world changes stepwise. Every robot changes its state either of the action rules defined later. Every obstacle, which is immobile in itself, can be *pushed* or *pulled* by robots.

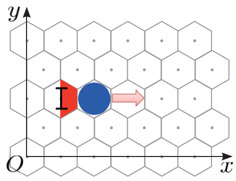
Now we propose the following rules for robot action. Push & Turn robots decide their movements from the information of two cells in front of the robot. Pull & Turn robots decides their movements from the information of two cells in front of the robot, and the back of the robot.

Rule 1 (Push & Turn rule)

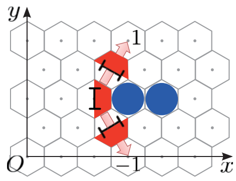
- **If the front cell is empty or exists one obstacle:** *step forward to the front cell (Figure 4(a)).*
- **Otherwise:** *turn* randomly *to the right or left. (Figure 4(b)).* •

Rule 2 (Pull & Turn rule)

- **If the front cell is empty:** *step forward to the front cell.*
- **Else if the front cell exists obstacle and back cell is empty:** *step backward to the back cell pulling one obstacle (Figure 5(a)).*
- **Otherwise:** *turn* randomly *to the right or left. (Figure 5(b)).* •

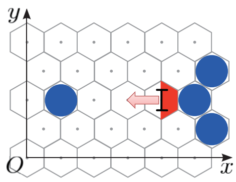


(a) Push (Move forward)

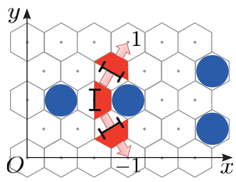


(b) Turn (Turn Right or left)

Figure 4: Push & Turn robot on hexagonal cellular space.



(a) Pull (Move backward)



(b) Turn (Turn Right or left)

Figure 5: Pull & Turn robot on hexagonal cellular space.

3. Basic Simulations

First, we carry out some basic simulations by each robot. Then we introduce an index to evaluate them.

3.1. Basic results: comparison between two rules

3.1.1. Push & Turn robots

In this case, suppose the field of 20×20 cells; 20 Push & Turn robots and 40 obstacles are distributed with random initial configurations. These robots movements eventually lead to obstacle clustering phenomena. Figure 6 shows some snapshots taken from a simulation result. First, the obstacles form small "core" clusters by about 500 steps. Then the cores tend to grow as the robots bring free obstacles. Some clusters are demolished into smaller fractions; some grow large enough so that they are "unbreakable" any more, and eventually absorb smaller fractions brought in by the robots. Most of the obstacles are formed into a single connected cluster by about 2000 steps (remember that the field has torus-like topology).

3.1.2. Pull & Turn robots

In this case, suppose the field of 20×20 cells; 20 Push & Turn robots and 40 obstacles are distributed with clustered initial configurations. These robots movements eventually lead to scatter obstacles. Figure 7 shows some snapshots of simulations. The clustered obstacles are scattered randomly by about 300 steps.

3.2. Indices for analysis

Let us begin with preparing an index for quantitative observation.

Definition 1 (Ratio of immobile obstacles) *Let $k \in \mathbb{N}$ be index for obstacles.* Degree of mobility of the k-th obsta-

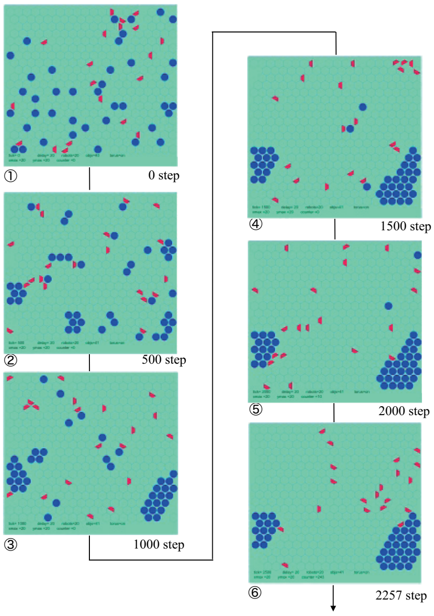


Figure 6: The 40 obstacles (blue objects) clustering simulation by Push & Turn robots (20 red robots) in spatial discretized system.

cle, *say* $M_k \in \{1, 2, 3, 4, 5, 6\}$*, is defined as the number of directions to that the obstacle can be pushed by a push & turn robot.*

Let $C \subseteq \mathbb{N}$ *be a subset of obstacle indices. The sum of degrees of mobility of obstacles in the subset, i.e.,*

$$M_C = \sum_{k \in C} M_k.$$

is called the degree of mobility *of the subset* C*. If* C *is the set of all obstacles, then* M_C *is simply denoted as* M *to imply the whole system's degree of mobility.*

The ratio of immobile obstacles I_M *is a set of obstacles whose degree of mobility* M_k *counts* 0 *for all obstacles.*

See Figure 8 for examples. When an obstacle ($k = 1$) can be moved to every direction (Figure 8(a)) the ratio of immobile obstacles I_M counts 0. When two obstacles $k \in C = \{1, 2\}$ are located next to each other (Figure 8(b)), I_M also counts 0. When an obstacle is surrounded by six obstacles (Figure 8(c)), then I_M counts 1.

4. Obstacle clustering by heterogeneous agents

This section describes the obstacle clustering by heterogeneous agents (Push & Turn robots and Pull & Turn robots).

4.1. Simulation: influence of the density of heterogeneous robots

Now let us turn to discuss the obstacle clustering at the difference of the density of Push & Turn robots to Pull & Turn robots. The size of the field is fixed to $100 \times 100 = 10000$ ($N = 100$). And the number of the obstacles is also fixed at 500 (5% of the field). The sum of Push & Turn robots and Pull & Turn robots are fixed at 1000. We examined by changing the density of the Pull & Turn robots from 1% to 10%.

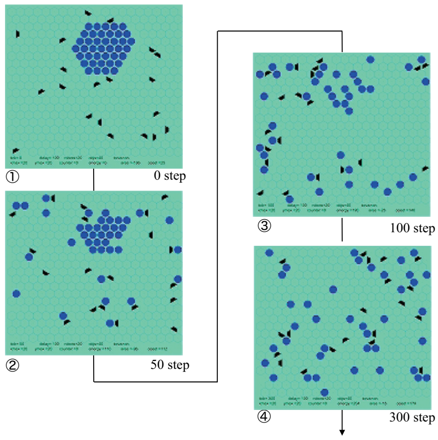
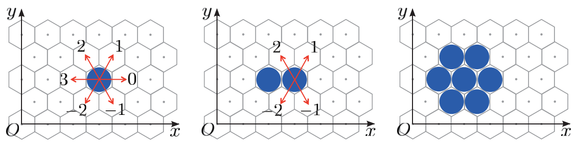


Figure 7: The 40 obstacles (blue objects) scattering simulation by Push & Turn robots (20 red robots) in spatial discretized system.



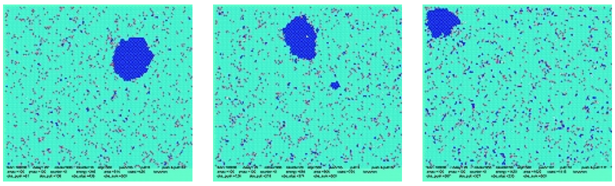
(a) $I_M = 0/1 = 0$ (b) $I_M = 0/2 = 0$ (c) $I_M = 7/7 = 1$

Figure 8: Examples: calculating the ratio of immobile obstacles.

Figure 9 shows the snapshots of the simulations at 100000 steps when the density of the Pull & Turn robots is 1, 2, 5%. And the changes of the ratio of immobile obstacles I_M are shown in Figure 10. The histograms of the ratio of immobile obstacles I_M from 90000 steps to 100000 steps are shown in Figure 11. Figure 11 indicates that the ratio of immobile obstacles I_M is at the dynamic equilibrium within some ranges. From Figure 9 and Figure 10, it seems that the ratio of immobile obstacles I_M gets smaller as the density of the Pull & Turn robots increases, and higher density of them leads to non-clustering of obstacles.

4.2. Numerical Analysis

The relationship between the ratio of immobile obstacles I_M and the density of the Pull & Turn robots is shown in Figure 12. Then, suppose the density of Pull & Turn robots as a independent valuable x, and the ratio of immobile obstacles I_M as a estimated variable y. And the relationship, fitted to a set of data, is characterized by a prediction equa-



(a) 1%　　(b) 2%　　(c) 5%

Figure 9: The obstacle clustering at the different density of heterogeneous agents.

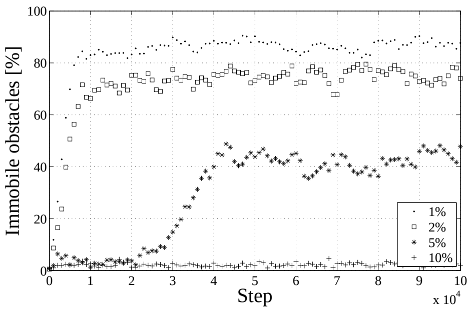


Figure 10: The changes of the ratio of immobile obstacles at the different density of heterogeneous agents.

tion.

$$
\begin{aligned}
y &= -13.2x + 102, \\
r^2 &= 0.917.
\end{aligned}
$$

From the above equations, it will be concluded that the ratio of immobile obstacles I_M can be controlled by feeding an input of the ratio of Push & Turn robots to Pull & Turn robots to the system.

5. Conclusion and future works

In this paper, we proposed a discrete-space version of obstacle clustering by distributed autonomous robots. From the quantitative analysis of obstacle clustering by heterogeneous robots (Push & Turn robots and Pull & Turn robots), it will be concluded that the ratio of immobile obstacles I_M can be controlled by feeding an input of the ratio of Push & Turn robots to Pull & Turn robots to the system.

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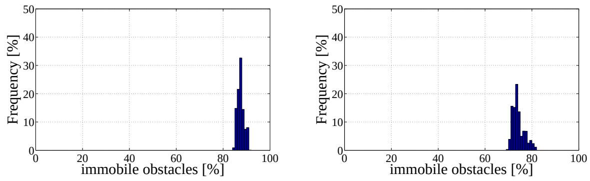
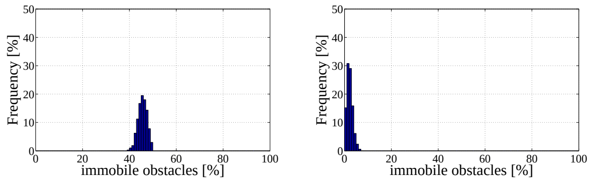


(a) 1% (average = 0.88)　　(b) 2% (average = 0.74)



(c) 5% (average = 0.46)　　(d) 10% (average = 0.024)

Figure 11: The histograms of the ratio of immobile obstacles at the different density of heterogeneous agents.

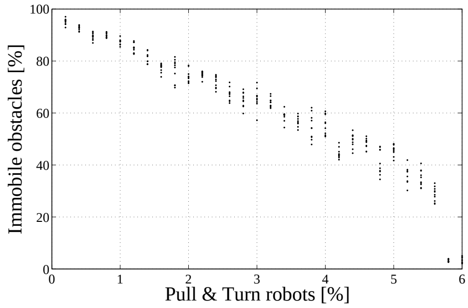


Figure 12: Density of the Pull & Turn robots v.s Ratio of immobile obstacles.

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