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Simulated decontamination experiments by mobile manipulator with visual recognition – Autonomous behavior driven by environment programming

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Abstract. Since Tohoku Earthquake off the coast of Pacific Ocean at Fukushima Prefecture and subsequent Tsunami devastated nuclear power station, No.1, in Fukushima, radioactive substances have been scattered off wide area of Fukushima. Then decontamination works have started, but they have not been progressing rapidly because there are not sufficient workers and they have risks that they should be exposed to radiation, which restrict working duration. So this research aims at developing a robot that moves and collects polluted soil by itself. This machine, controlled by visual information, recognizes and collects simulated contaminated soils automatically, where Model-based Matching Method and Genetic Algorithm are used to recognize the contaminated-soil-model. In this paper, recognition methods, structure of mobile manipulator with hand-eye cameras and results of simulated decontamination experiments are reported, in which a concept of autonomous behavior driven by "Environment Programming," meaning that environment gives programmed commands to the autonomous mobile manipulator.

Keywords: Model-based matching method, genetic algorithm, decontamination

1. Introduction

By the 2011 off the Pacific coast of Tohoku Earthquake that occurred on March 11, 2011, Fukushima Nuclear Power Plant No. 1 became a critical state, and radioactive particles have been scattered by hydrogen explosions.

Even though decontamination works have started and have extended vigorously by human workers in Tohoku regions, the contamination levels have not been reduced enough to allow people to come back their original home towns because radioactive substances still remain in soils at mountain and muds precipitated at bottoms of lake in Fukushima prefecture. Since the workers have risks of being exposed to radioactive rays during the decontamination, the decontamination tasks are not conducted as planned schedules, which further delay the full fledged coming back of indigenous people who wants to settle there again. Therefore, such dangerous decontamination tasks should be better conducted by automatic robots, where the robots may be able to use Gamma Ray Camera to detect gamma rays emanating from

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radioactive substances. So how to constitute autonomous robots that can collect radioactive soil and can assure that the contamination level becomes below the allowable level, less than 20[mSv].

In this presentation, a concept of "autonomous behavior driven by Environment Programming" that environment give programmed commands to the autonomous mobile manipulator is proposed. Based on the concept, we have conducted experiments to collect the green particles that mock contaminated soil emanating radiation detected by Gamma Ray Camera. Since the green particles (GPs) can be seen by ordinary camera, so this research aims at developing a robot that moves and collect polluted soil by oneself with visual servoing. Visual servoing is a control method of robot's motion through visual information in the feedback loop, which is obtained from visual cameras [1–4]. Some methods have already been proposed to improve observation abilities, by using stereo cameras [5], multiple cameras [6], and two cameras; with one fixed on the end-effector, and the other set in the workspace [7]. These methods obtain different views to observe the object by increasing the number of cameras, leaving the system less adaptive for changing environment. This paper verifies the effectiveness of decontamination experiments by proposed autonomous behavior driven by Environment Programming.

2. Recognition method

2.1. Three dimensional model-based matching method

2.1.1. Optimization by genetic algorithm

The images input from video cameras are composed by hue value ranging from 0 to 255. A three dimensional (3D) searching model comprises inside spaces $S_{R,in}(\underline{\phi})$ and $S_{L,in}(\underline{\phi})$–$S_{R,in}(\underline{\phi})$ is right camera model and $S_{L,in}(\underline{\phi})$ is left one and $\underline{\phi}$ represents pose (position and orientation) of the 3D target object – and the strips spaces $S_{R,out}(\underline{\phi})$ and $S_{L,out}(\underline{\phi})$ in order to evaluate differences of hue value between circumferences and the objects indicating simulated radioactive substances. The hue value of right image at the position ${}^{IR}\bar{\boldsymbol{r}}_{i,j}$ is expressed as $p({}^{IR}\bar{\boldsymbol{r}}_{i,j})$, and the hue value of left image at the position ${}^{IL}\bar{\boldsymbol{r}}_{i,j}$ is expressed as $p({}^{IL}\bar{\boldsymbol{r}}_{i,j})$. Equation (1) shows the fitness function [8] that calculates the correlation function between the 3-D search model and objects in the left and right images [9].

$$F_{ss}(\underline{\phi}) = \left\{ \Bigg(\sum_{{}^{IR}\bar{\boldsymbol{r}}_{i,j} \in S_{R,in}(\underline{\phi})} p({}^{IR}\bar{\boldsymbol{r}}_{i,j}) - \sum_{{}^{IR}\bar{\boldsymbol{r}}_{i,j} \in S_{R,out}(\underline{\phi})} p({}^{IR}\bar{\boldsymbol{r}}_{i,j}) \Bigg) \right.$$
$$\left. + \Bigg(\sum_{{}^{IL}\bar{\boldsymbol{r}}_{i,j} \in S_{L,in}(\underline{\phi})} p({}^{IL}\bar{\boldsymbol{r}}_{i,j}) - \sum_{{}^{IL}\bar{\boldsymbol{r}}_{i,j} \in S_{L,out}(\underline{\phi})} p({}^{IL}\bar{\boldsymbol{r}}_{i,j}) \Bigg) \right\} /2 \tag{1}$$

The 3-D models with assumed pose defined by genes in Genetic Algorithm (GA) are projected to left and right images, and they are to be evolve in the direction that make the models have higher correlation values defined by Eq. (1). There is no guarantee that the genes in GA processes can give the pose of the highest peak of the fitness function corresponding to the true pose of object, but GA can make efforts to find maximum peak and also the pose to give the peak under the conditions with lighting condition being changing [10,11]. Furthermore, we can set a model and lighting environments to make the fitness function have a peak that is given by the gene whose pose corresponding to the true target pose. Then it can be thought reasonable to assume in this paper that the variables of gene giving highest peak of the fitness function represents the true pose of the target object, changing pose detection problem into optimization problem.

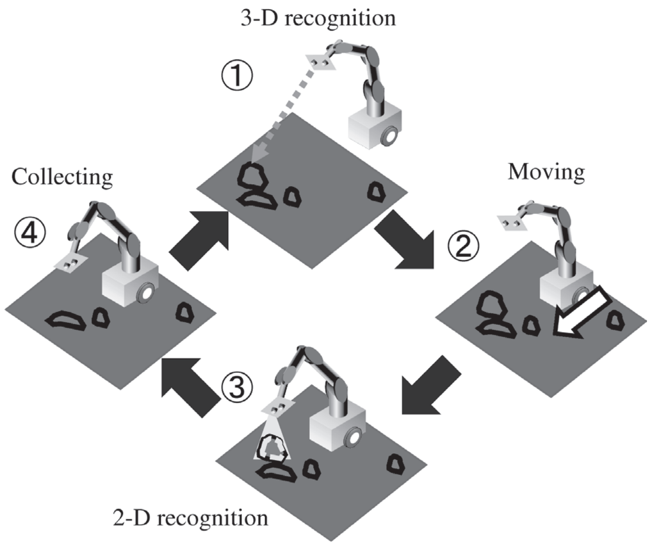

Fig. 1. Decontamination process composed of (1) finding 3D position of GPs, (2) approaching there, (3) reconfirming the 2D position when the hand-eye camera of the mobile manipulator looking down the GPs from just above the GPs' position, (4) sucking the GPs by cleaner.

The values of the individual genes means the possible solution representing the pose of the target object in the Model-based Matching method [5]. Each individual gene value allows to calculate its corresponding fitness value, and the genes are evolved based on the fitness values [12]. The processes are performed based on the superiority or inferiority of this value, and a set of the next generation is generated through GA's process. The fitness value in the generation is higher than the former one, that is, it approaches toward the maximum neighborhood of the fitness function showing object. By repeating this processing, GA discovers the maximum peak in the fitness distribution, which indicates the true pose of target object, meaning that the evolving process can find contaminated soil areas.

3. Concept of decontamination process – Autonomous behavior driven by environment programming

Decontamination process is shown in Fig. 1. The mobile manipulator has a hand eye camera that imitates Gamma Ray Camera, which can detect radioactive substances in the video camera images that can be seen as red color. In this simulated decontamination experiments, the radioactive substances are mocked by green sphere particles with radius of 5[mm].

The task that the mobile manipulator is required to complete is to remove all green particles completely until extinction. If the robot should have abilities of (1) searching green particles, (2) moving to the place where the particles exist, (3) removing them, (4) confirming whether there remain the particles or not, then the robot can continue the decontamination process until the particles are being extincted. Since the robot has a character to continue the process (1)–(4) until completion, the existence of the particle can be interpreted that it indicates the robot where the particles exist and to eradicate the remaining residues until completion. This robot's procedures are just to repeat finding, approaching, removing and finding repeatedly again and again, which is a view from the robot side. Contrarily another possible point of view is that the distribution of contaminated substances commands the robot to come near and

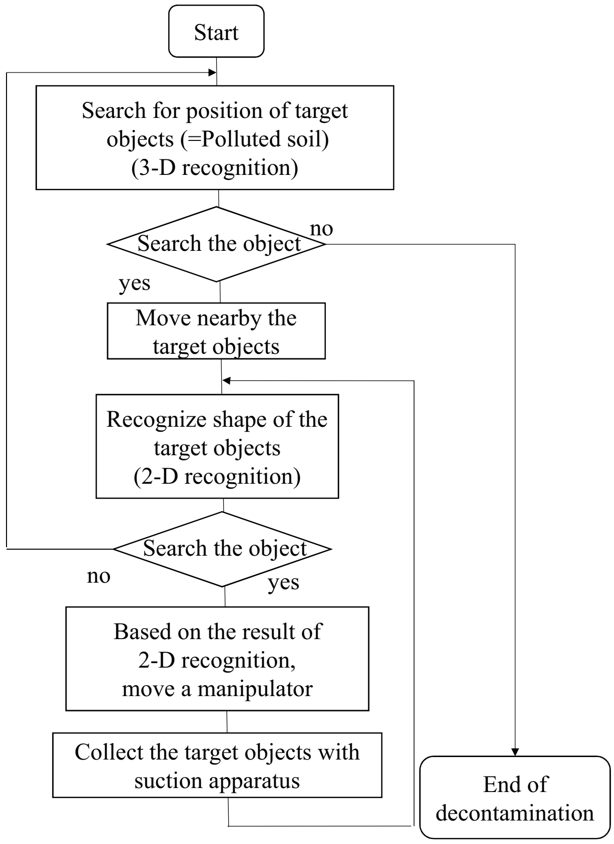

Fig. 2. Flowchart of autonomous behavior driven by environment conditions interpreted as instructions like programming, which can be thought to be environment programming.

to remove them completely. In this view point, since the contaminated substances are thought to be commanding to the robot to remove, then the environment can be thought to be a program to instruct the robot to decontaminate. Then we think we can recognize the environment is equivalent to a program, having named as “Autonomous Behavior driven by Environment Programming.”

The process can be divided into following 4 parts roughly as shown in Fig. 1. The numbers that are written in Fig. 1 are corresponding to the numbers listed. (1) By using 3D recognition, recognize pose of target objects; finding: (2) Approach to the object and move end-effector just above the objects; moving: (3) Look down and recognize the objects by using 2D recognition; finding again: (4) Lower the suction nozzle and vacuum particles; removing. The mobile manipulator repeats above tasks until no particle remains. The process of the decontamination task, which simply repeats above each operation are depicted by the flowchart as shown in Fig. 2.

4. Decontamination experiments

4.1. 3D recognition and pose estimation and approaching

The mobile manipulator used for simulated decontamination is shown in Fig. 3. This mobile manipulator is composed of mobile robot with two wheels whose velocities are driven independently, mounted

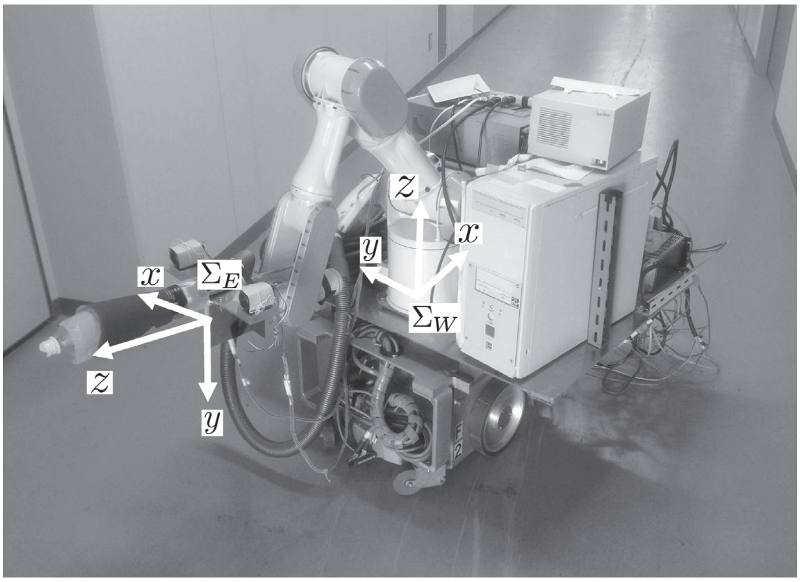

Fig. 3. Mobile manipulator with a sucking head, and vehicle coordinates Σ_W fixed at the base link of mounted manipulator hand coordinates Σ_E.

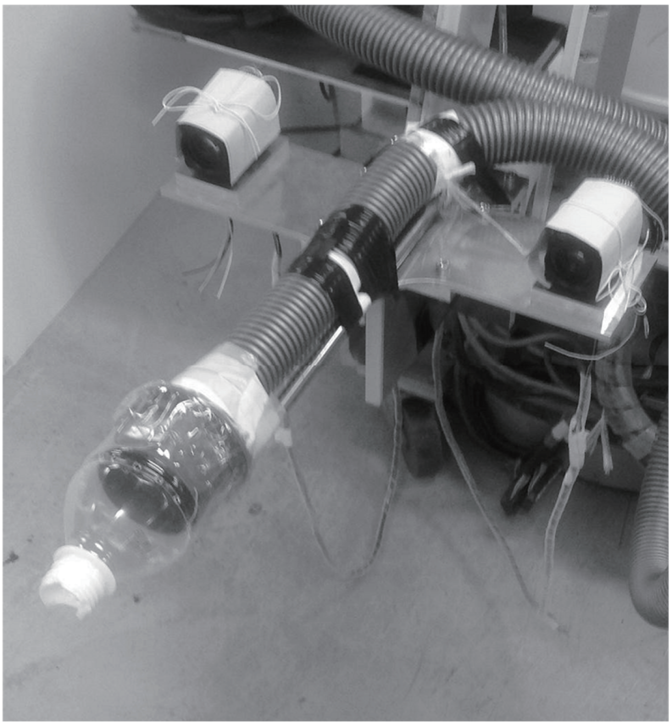

Fig. 4. Manipulator's end-effector with sucking nozzle of cleaner.

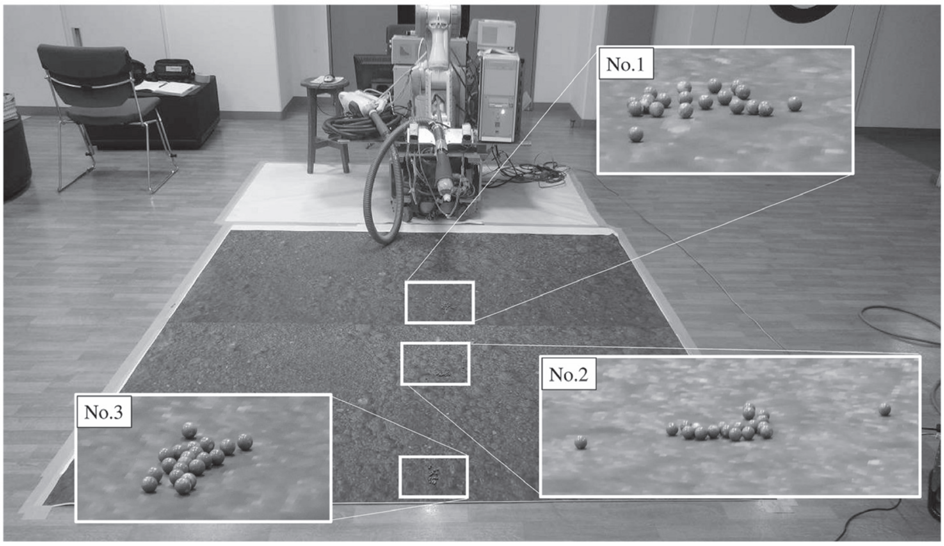

Fig. 5. Experimental condition for 3D recognition of green particles placed on soil-photographed-printed clothes with three groups of particles.

manipulator with hand-eye cameras, a vacuum cleaner sucking up the GPs, a PC and so on. The hand-eye cameras and a suction nozzle set at manipulator's end-effector are shown in Fig. 4.

Experiment condition is shown in Fig. 5. Three groups of GPs are scattered on clothes on which photographs of the soil – size is 2000 mm square – are printed. Each GP group is composed of 20 particles. The relationship between mobile manipulator's position and GPs' position are shown in Fig. 5. The GPs' positions are $(x, y, z) = (-1200, 0, -420)$, $(-1700, 0, -420)$, $(-2300, -60, -420)$ [mm] in Σ_W shown in Fig. 3 that is a coordinates fixed at the space where the mobile manipulator be set at the start initial position depicted at Fig. 6(a). In this experiment the behavior to approach to the GPs' position is the first objective, and the consecutive sucking operations will be conducted based on the 2D recognition results as explained in next section.

The manipulator recognizes three GPs' position by using 3D recognition and approaches to the positions successfully as shown in Fig. 6. In this 3D recognition two cameras images are indispensable to detect the 3D position of the GPs. Model-based matching method with dual eye system [10,11] has been confirmed to be effective to measure 3D positions of GPs through left and right camera images shown at the right-hand side of the Fig. 6. The errors between true GPs' positions and 3D recognized position have been confirmed. The x-direction error in Σ_W shown in Fig. 3 ranges from -200 to 100[mm], the y-direction from -60 to 150[mm], and the z-direction from -170 to 150[mm]. By referring the detected 3D positions, the mobile manipulator proceeds its position to the place to suck up the GPs as shown in the left side of the Fig. 6.

The x-direction and y-direction errors will not make a problem because the positions recognized can be compensated later by 2D recognition, where the hand-eye camera can recognize the targets by using 2D recognition while the camera looking down the particles vertically, the geometric relation enables the camera system to allow the 2D recognition is enough to detect 3D positions of GPs. The z-direction error is also not problem in this experiment, since the assumed ground is flat. But if the manipulator works on the rough ground, the proposed procedure thought to be applicable, then 3D recognition should be repeat again at the the situation (3) in Fig. 1.

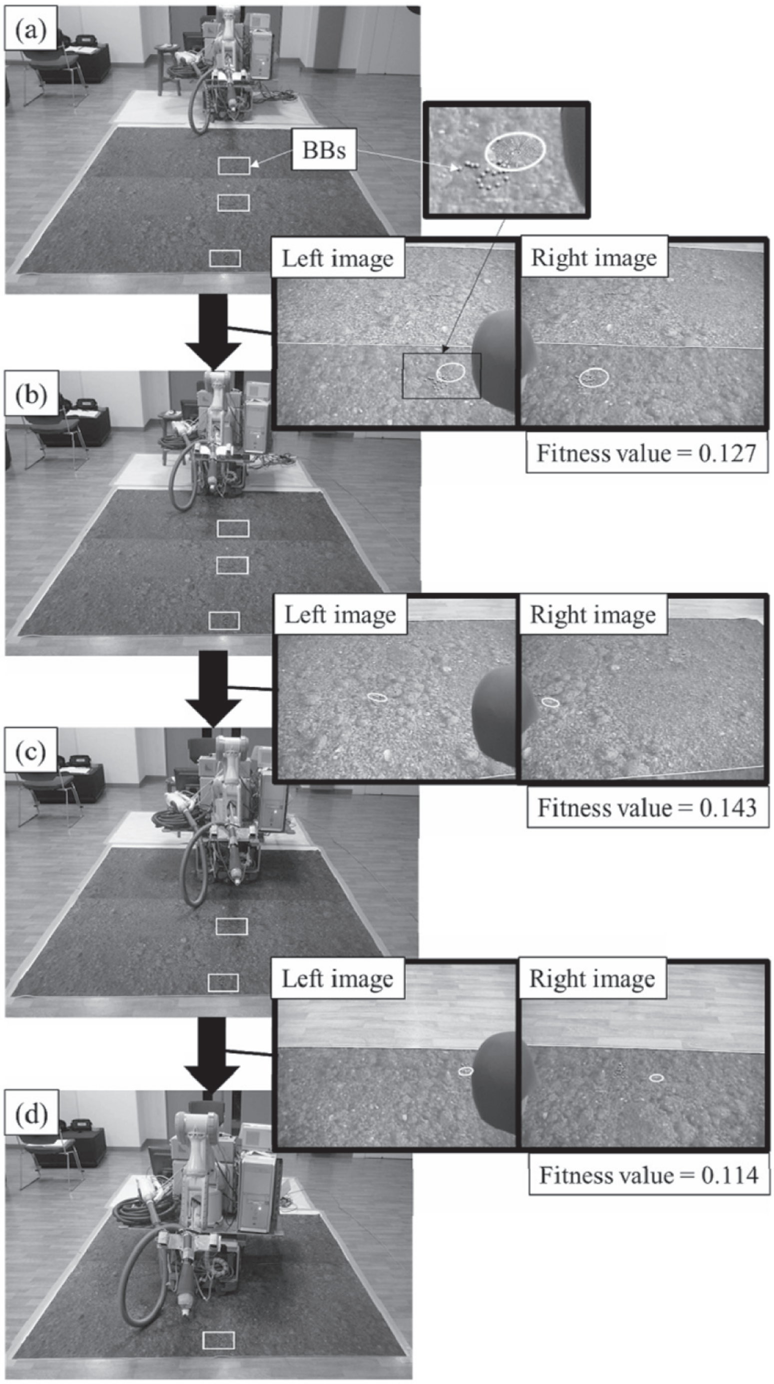

Fig. 6. 3D recognition and approaching experiments. After the mobile manipulator moving toward the GPs, it suck up the GPs through suction nozzle based on 2D recognition.

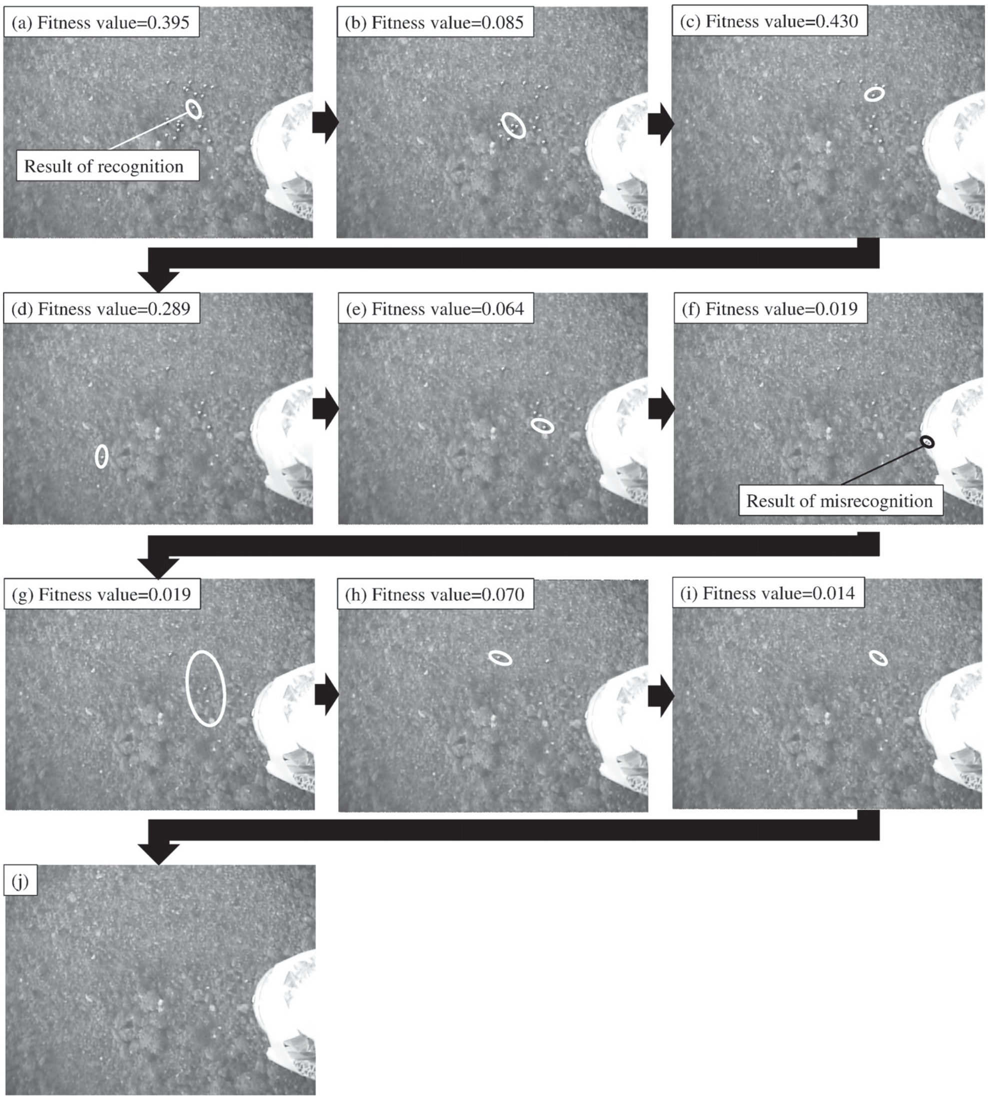

Fig. 7. Images of hand-eye 2D recognition results with repeated sucking procedures, which succeeded to suck GPs until extinction.

4.2. 2D recognition and decontamination experiment

In this section, experiments to confirm sucking ability based on 2D position detection. The three groups of GPs are placed as shown in Fig. 5 and the vehicle's position after approaching the sucking place based on the 3D positions are shown in Fig. 6, which shows that the mobile manipulator has proceeded the place where it can look down the particles just above the place of the GPs. Then the remaining problem is whether the sucking nozzle can be guided to the place just above the group of GPs and sucking them until it extinguish them, which is the most important.

The manipulator continue those actions (1)–(4) until all GPs would have been sucked, i.e., been decontaminated. In this simulated decontamination experiment the procedures (1)–(4) were repeated three times to complete the decontamination.

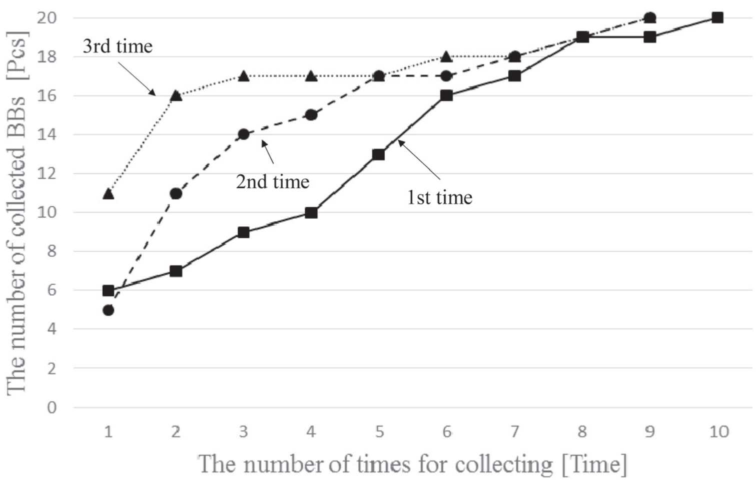

Fig. 8. Relationship between the number of sucked particles and the number of sucking trials. The total number of the particles is twenty, having certified the sucking all particles is successfully completed.

The results are shown in Fig. 7. In this figure, the results of 2-D recognition are expressed with white ellipse. In Figs 7(a)–(e), it is shown that GPs are recognized and collected certainly by the manipulator. But in Fig. 7(f), the manipulator recognized them mistakenly. But they are recovered to be recognized again as shown in Fig. 7(g), and it recognized GPs certainly in Figs 7(h)–(i). At last, there is no GPs in Fig. 7(j).

In addition, a relationship between the number of collection and the number of collected GPs is shown in Fig. 8. This figure shows all GPs are collected completely in all 3 times of experiments.

5. Discussion

According to the results of experiments, the mobile manipulator has the abilities for 3-D recognition, Movement, 2-D recognition and collection. But there are some problems that were found newly. For example, the Fig. 7(f) shows the manipulator recognizes mistakenly. More examples, the fitness functions were low as shown in Fig. 6. It shows that the manipulator has a possibility to recognize mistakenly and move to a wrong direction. These problems should be solved, so something, such as the conditions of genetic algorithm, the angles of cameras, the position of the manipulator and so on, will be changed and experiments will be conducted again and again.

6. Conclusion

In this paper, it has been confirmed the mobile manipulator was performed to complete simulated particle of contaminated radioactive substances until extinction with full automation driven the proposed autonomy, that is, "Autonomous Behavior driven by Environment Programming."

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