

Formation Behavior of Multiple Robots based on Tele-operation

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Abstract: Recently, multi-robot systems have been discussed to realize a large size of distributed autonomous system. Furthermore, multi-robot systems have been applied to various problems such as autonomous guided vehicles, soccer robots, and search and rescue system by multi-robot. This paper proposes intelligent formation behavior for the multi-robot based on sensor fusion. First, we discuss multi-agent systems and wireless network technologies. Next, we explain the hardware specification of robot and tele-operated system and wireless communication. Finally, we show experimental results, and discuss the availability of intelligent formation behavior for multi-robot.

Keywords; *Multiple Robots, Formation Behaviors, Fuzzy Control, Tele-operation*

I. INTRODUCTION

Recently, various types of intelligent multi-agent systems have been proposed to realize a large size of autonomous systems [1-8]. Multi-agent systems have been applied to various problems such as autonomous guided vehicles, soccer robots, and search and rescue system by multi-robot. Network robots are also assumed as one of multi-agent systems. We should discuss two different types of problems in multi-agent systems simultaneously. The first one is the relationship of each agent with its environment from individual point of view. The other is the internal relationship among agents with their outer environmental conditions from the collective point of view. Furthermore, intelligent technologies including fuzzy, neural network, and evolutionary computing, have been applied to such the intelligent systems interacting with environments [9-13]. However, the high level of integration of the collective intelligence and individual intelligence has not discussed much yet. Therefore, we proposed the formation control methods for multi-robot system, and discussed the applicability of the proposed methods in various environmental conditions [14-17]. However, we did not use multiple mobile robots in real world conditions on network technologies.

As the progress of wireless network technologies and ubiquitous computing, various types of network robots have been developed [18-21]. The research on wireless sensor networks combines three components of sensing, processing, and communicating into a single tiny device. The ubiquitous

computing integrates computation into the environment. The ubiquitous computing is conceptually different from sensor network, but both aim at the same research direction. Sensor networks and ubiquitous computing have been incorporated into robotics. These researches are called network robotics and ubiquitous robotics, respectively. If the robot can receive the environmental data through the network without the measurement by sensors, the size of the robot can be easily reduced and the received environmental data are more precise because the sensors equipped in the environment are designed suitable to the environmental conditions. The available communication channels are limited under the real world conditions. Therefore, we apply different standards of network channels, e.g., ZigBee for the network communication among mobile robots, and between a host computer and mobile robots.

Furthermore, we discuss the formation behavior based on available sensing data. Next, we explain the multi-objective behavior coordination, and we propose the sensor fusion method based on various types of sensor inputs. Next, we propose monitoring system to enable environmental measurement under unknown environment by using multi-robot. Finally, we show several experimental results of the proposed method.

II. TELE-OPERATION OF MULTIROBOT

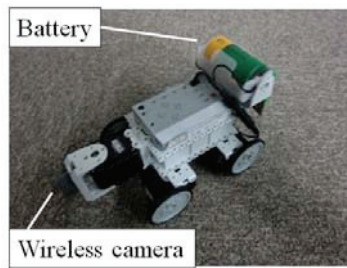
A. A Mobile Robot for Information Seeking

We developed various types of mobile robots using Bioloid [22]. The robot can perform the wireless communication by ZigBee with host computers or other robots. Figure 1 shows developed the mobile robots developed in this paper. This leader robot is controlled by the manual operation with a joystick. The first mobile robot shown in Fig.1 (a) equips a wireless camera. The size of the robot in Fig.1 (a) is 140 x 120 x 90 [mm].

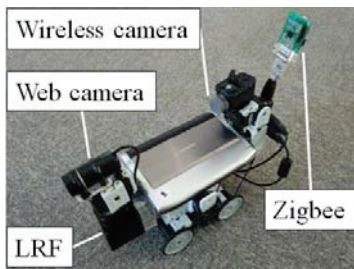
The follower robot shown in Fig.1 (b) equips two cameras and a laser range finder (LRF). Furthermore, the small size of PC is attached on the robot to perform autonomous behavior by using web camera and LRF. This robot constructs a formation according to the position of the leader robot. One wireless camera is used for the expanding view area for the human operator in order to present the area surrounding the

leader robot. Another camera is used for the target tracing behavior, and LRF is used for collision avoidance behavior. The size of the robot in Fig.1 (b) is 300 x 150 x 250 [mm]. The communication range of the wireless camera and ZigBee with the host computer is 30 [m]. ZigBee is one of the Near Field Communications (NFC) suitable to short range and high frequency communication for home appliances. Moreover, the ZigBee can form various types of network topologies such as star type, tree type and mesh type according to the aim and environmental conditions.

Table 1 shows the specification of two robots. A human operator sends a control command to the leader robot from the host computer based on images received directly from the wireless camera.



(a) A leader robot



(b) A follower robot

Figure 1. Tele-operated mobile robots

TABLE I. SPECIFICATION OF TWO ROBOTS

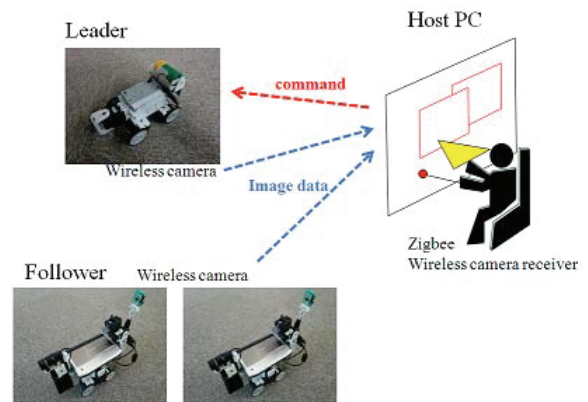
Type	Leader	Follower
Weight	0.8kg	2.0kg
Speed	Max 1.7 m/s	Max 1.8 m/s
Sensor	Wireless camera	Wireless camera Web camera LRF
Operation method	Manual (Joystick)	Autonomous

B. Tele-operation system

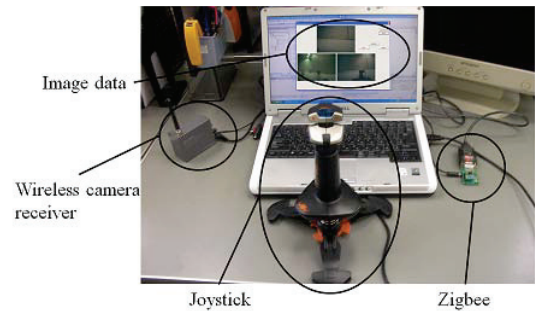
We developed a human interface for the tele-operation based on graphical user interface (GUI) from the host computer. The image data of wireless camera equipped with the leader robot are transmitted to the host computer, and the operator can monitor those data (Fig.2 (a)).

The behaviors of the leader robot are based on the semi-autonomous control. Figure 2 (b) shows a snapshot of the control of the robot by the operator. The operator can navigate the leader robot by using a joystick. The collision avoidance and target trace of the follower robot with obstacles are done automatically. Therefore, the operator can focus on the monitoring of the environment with the low human load of navigation based on the semi-autonomous control mode.

Figure 2 (c) shows the user interface for the remote monitoring and remote control of three mobile robots. A view image from the leader robot is displayed in the upper on the screen, and that from the follower robot is displayed in the lower left and right. The operator can see the facing situation from the camera of the leader robot from the local point of view, while he or she can see the surrounding situation from the camera of the follower robot from the global point of view. In this way, the operator can control these mobile robots by changing the viewpoint of an operator.



(a) The information flow in the tele-operation



(b) The control of the pan-tilt mechanism by touch panel



(c) Camera images of tele-operated mobile robots in the monitoring display

Figure 2. Tele-operation system

C. Formation Behaviors

The multi-robot system should update the shape of formation according to the aim of information seeking under the features of environmental conditions, e.g., unknown, dynamic, and/or unreliable. For example, we show five types of shapes of formation in Figure 3 where the number of robots is 3, the equipped sensors are camera and LRF, and blue fan-shaped area and green fan-shaped area mean the measurable ranges by LRF and wireless camera, respectively.

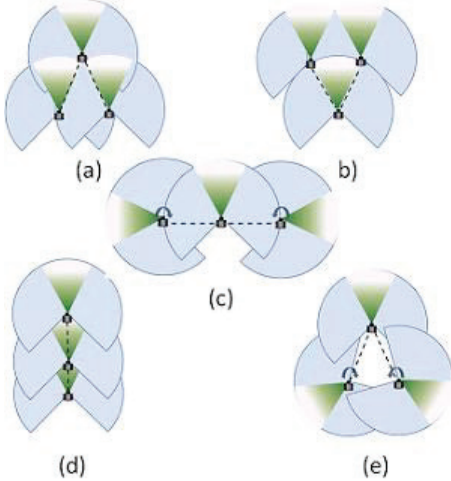


Figure 3. various type of formation

Figure 3 (a) is a basic triangular formation by three robots where one leader robot and two follower robots. The operator controls the leader, while two follower robots gather their surrounding environmental information. Figure 3 (b) shows a formation in unknown or dangerous environment where the two top followers gather the environmental information in order to detect dangerous state and others, and the operator controls the leader robot from the backward. Figure 3 (c) shows a formation of three robots arranged in a single horizontal row. This formation

can gather wide range of images to display the global environmental state at a glance. Figure 3 (d) shows a formation of three robots arranged in a single tandem line in a narrow path, small space, and many obstacles. Figure 3 (e) shows a formation of three robots to observe all-around view in dynamic or changing environment when three mobile robots stop at a point. In this way, we can change the formation of robots according to the aim of information seeking under different environmental conditions. In this paper, we focus on the basic triangular formation behavior as the first step of this study.

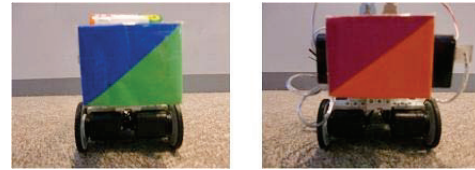
III. FORMATION BEHAVIORS

A. Functions for Formation Behaviors

Each robot needs to understand its relative position with other robots to build the global formation shape by multiple robots. Consequently, the robot should localize the self-position relative to its neighboring robots, and share the information on position and posture with other robots. A dead-reckoning algorithm is often used to estimate the global self-position, but this method has a problem of accumulating errors in the estimation. Therefore, we use web cameras and LRF for the relative localization. The web camera image is used for relative localization, and the wireless camera image is used for remote monitoring and control by a human operator.

B. Object Detection

Various types of pattern recognition methods and image processing methods have been proposed [23-30]. We applied the continuously adaptive mean shift (CAMSHIFT) algorithm using Open CV library to extract the landmark of the leader mobile robot from the camera image of the follower mobile robot. Because the basic CAMSHIFT algorithm updates the target template sequentially, it is difficult to trace a target landmark if the mobile robot fails to recognize the current target template.



(a) Leader robot

(b) follower robot

Figure 4. Landmarks used for visual tracking

In order to detect and identify other robots, we use landmark identifiers based on combination of two different colors (Fig.4). We use a steady-state genetic algorithm (SSGA) for object detection as one of search methods, because SSGA can easily obtain feasible solutions through environmental changes with low computational cost. SSGA simulates a continuous model of the generation, which eliminates and generates a few

of individuals in a generation (iteration). A template is composed of numerical parameters of $g_{i,1}$, $g_{i,2}$, $g_{i,3}$, and $g_{i,4}$. The number of individuals is G . One iteration is composed of selection, crossover, and mutation. The worst candidate solution is eliminated ("Delete least fitness" selection strategy), and is replaced with the candidate solution generated by the crossover and the mutation. We use the elitist crossover and adaptive mutation. The elitist crossover randomly selects one individual and generates an individual by combining genetic information from the randomly selected individual and the best individual. Next, the following adaptive mutation is performed to the generated individual,

$$g_{i,j} \leftarrow g_{i,j} + \left(\alpha_j + \frac{f_{\max} - f_i}{f_{\max} - f_{\min}} + \beta_j \right) \cdot N(0,1) \quad (1)$$

where f_i is the fitness value of the i th individual, $f_{\max}$ and $f_{\min}$ are the maximum and minimum of fitness values in the population; $N(0,1)$ indicates a normal random variable with a mean of zero and a variance of one; α_j and β_j are the coefficients ($0 < \alpha_j < 1.0$) and offset ($\beta_j > 0$), respectively. In the adaptive mutation, the variance of the normal random number is relatively changed according to the fitness values of the population.

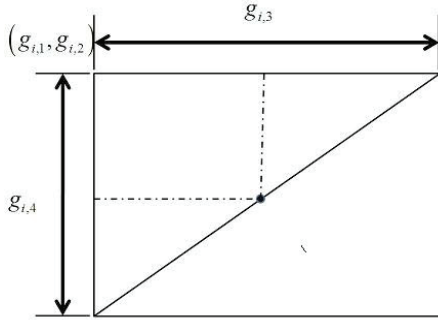


Figure 5. A candidate solution for object detection

The template of each candidate solution is evaluated as the sum of local evaluations in small subareas shown in Fig.6. Each subarea is evaluated by different weights in the following;

$$f_i = \sum_{a=1}^{n_1} \sum_{b=1}^{n_2} \sum_{c=1}^{n_3} M_{a,b,c} C_{a,b,c} \quad (2)$$

where $C_{a,b,c}$ and $M_{a,b,c}$ are the number of pixels of the c th color in the subarea (a,b) , and its evaluation weight. We can perform the search of landmarks with different color distribution. If the fitness value of the best candidate solution is higher than the predefined threshold, its corresponding template is recognized as the target landmark. The position (u,v) of the landmark in the local coordinate on the camera image is calculated as

$$(u,v) = \left(g_{b,1} + \frac{g_{b,3}}{2}, g_{b,2} + \frac{g_{b,4}}{2} \right) \quad (3)$$

where b is the best candidate solution. The relative angle (ξ) between the moving direction of the follower robot and the position of the leader robot is calculated by

$$\xi = \tan^{-1} \left(\frac{2 \cdot u \cdot \tan \frac{\omega}{2}}{Q} \right) \quad (4)$$

where the size of pixels on the camera image is $P \times Q$, ω is the view angle of the web camera in Fig.7. Next, we obtain the distance information (L_{leader}) by referring to the distance measured by LRF.

$M_{1,1,c}$		
	$M_{a,b,c}$	
		$M_{n_1,n_2,c}$

Figure 6. A template matching evaluation using subarea

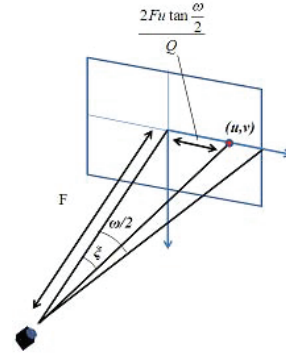


Figure 7. Estimation of the relative angle

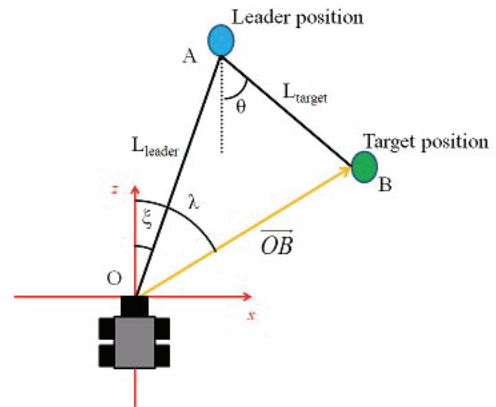


Figure 8. Estimation of the relative position

C. Multi-Objective Behavior Coordination

Various types of intelligent control methods for mobile robots have been proposed such as production rules, Bayesian networks, neural networks, fuzzy inference systems, and classifier systems [31-34]. We have applied fuzzy inference systems to represent behavior rules of mobile robots, because the behavioral rules can be designed easily and intuitively by human linguistic representations. A behavior of the robot can be represented using fuzzy rules based on simplified fuzzy inference [31]. In general, a fuzzy if-then rule is described as follows,

If x_1 is $A_{i,1}$ and ... and x_M is $A_{i,M}$
Then y_1 is $w_{i,1}$ and ... and y_N is $w_{i,N}$

where $A_{i,j}$ and $w_{i,k}$ are the Gaussian membership function for the j th input and the singleton for the k th output of the i th rule; M and N are the numbers of inputs and outputs, respectively. Fuzzy inference is performed by,

$$\mu_{A_{i,j}}(x_j) = \exp\left(-\frac{(x_j - s_{i,j})^2}{t_{i,j}^2}\right) \quad (5)$$

$$\mu_i = \prod_{j=1}^M \mu_{A_{i,j}}(x_j) \quad (6)$$

$$y_k = \frac{\sum_{i=1}^R \mu_i w_{i,k}}{\sum_{i=1}^R \mu_i} \quad (7)$$

where $s_{i,j}$ and $t_{i,j}$ are the central value and the width of the membership function $A_{i,j}$; R is the number of rules. Outputs of the robot are output levels of the left and right motors ($N=2$). Fuzzy controller is used for collision avoidance and target tracing behaviors. The inputs to the fuzzy controller for collision avoidance are the measured distance to the obstacle by LRF. The inputs to the fuzzy controller for target tracing are the estimated distance to the target point and the relative angle to the target point from the moving direction ($M=2$).

In general, a mobile robot has a set of behaviors for achieving various objectives, and must integrate these behaviors according to the environmental conditions. Therefore, we proposed the method for multi-objective behavior coordination [14,15]. The multi-objective behavior coordination can integrate outputs of several behaviors according to the time-series of perceptual information, while the original subsumption architecture selects one behavior [13]. This multi-objective behavior coordination is composed of a sensory network, behavior coordinator, and behavior weight updater. The sensory network outputs perceptual information based on sensing data and updates the parameters of sensors recursively according to the perceptual information [33]. A behavior weight is assigned to each behavior. The output is calculated by

$$y_k = \frac{\sum_{j=1}^K wgt_j(t) \cdot y_{j,k}}{\sum_{j=1}^K wgt_j(t)} \quad (8)$$

where K is the number of behaviors; $wgt_j(t)$ is a behavior weight of the j th behavior over the discrete time step t . By updating the behavior weights, the robot can take a multi-objective behavior according to the time series of perceptual information. The update amount of each behavior is calculated as follows,

$$\begin{bmatrix} \Delta wgt_1 \\ \Delta wgt_2 \\ \vdots \\ \Delta wgt_K \end{bmatrix} = \begin{bmatrix} dw_{1,1} & dw_{1,2} & \cdots & dw_{1,L} \\ dw_{2,1} & & \ddots & \\ \vdots & & & \vdots \\ dw_{K,1} & & \cdots & dw_{K,L} \end{bmatrix} \begin{bmatrix} si_1 \\ si_2 \\ \vdots \\ si_L \end{bmatrix} \quad (9)$$

where si_i is the parameter on the perceptual information; L is the number of perceptual inputs. This method can be considered as a mixture of experts if the behavior coordinator is considered as a gating network.

IV. EXPERIMENTAL RESULTS

This section shows several experimental results of the proposed method. We use one leader robot for tele-operation and two follower robots to extend the view area for the monitoring and control by human operators. The size of the experiment environment is 3,000 [mm] $\times$ 7,000 [mm] including three obstacles. The suitable distance between two robots is set at 500 [mm]. The number of candidate solutions in SSGA is 50; the number of evaluations is 1,500 (corresponding to 30 iterations of discrete generations). If the fitness value of the best candidate solution is larger than 200, its corresponding template is considered as a detected landmark, and the mobile robot traces the rear of the leader robot with the predefined relative angle.

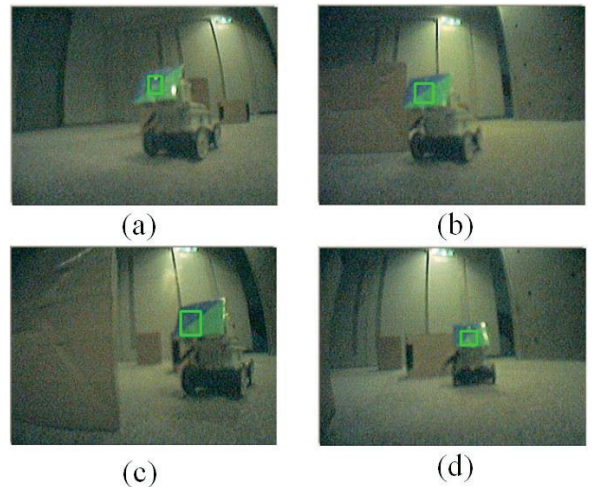


Figure 9. Follower's camera view

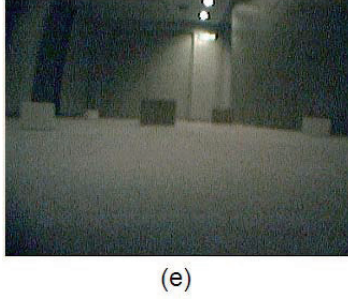


Figure 10. Leader's camera view

First, we show experimental results of image processing for target tracing. Figure 9 shows an experimental result of image processing by SSGA for landmark detection using camera images of the follower robot where a green frame indicates the detected landmark attached with the leader robot. Furthermore, the human operator can understand the environmental state in front of the leader robot, but this image is not enough to control the leader robot (Fig.10). On the other hand, the image from the follower robots includes the environmental state surrounding the leader robot (Fig.11 (a)-(d)). Therefore, the human operator can easily understand the situation of the leader robot, and can control the leader robot by using two types of images from the leader robot and follower robots.

Next, we show experimental results of tandem formation behavior of three robots. Figures 11 and 12 show overview of an experimental result of tele-operation and images sent from robots, respectively. In Figure 11 (d), the solid and dotted lines indicate the trajectories of the leader robot and follower robots, respectively. The follower robot traces the rear of the leader robot by extracting the landmark with keeping the suitable distance with the leader robot, while avoiding the collision with other obstacles. Figure 13 shows the change of fitness value and the degree of danger in the tandem formation behavior of second robot (Follower 1). In the experimental result, since the fitness value is larger than threshold (200) for the target tracing, the robot successfully traces the rear of the leader robot. The behavior weight is updated according to the degree of danger calculated by the minimal distance to obstacles. If the value is high, the behavior weight for collision avoidance is high. The motor output signals are calculated every 300 msec. In the experimental result, because the degree of danger is high, the follower robot tried to avoid the collision. As a result, the fitness value is not so high because the ratio of target tracing behavior is not high (Figure 11 (d)).

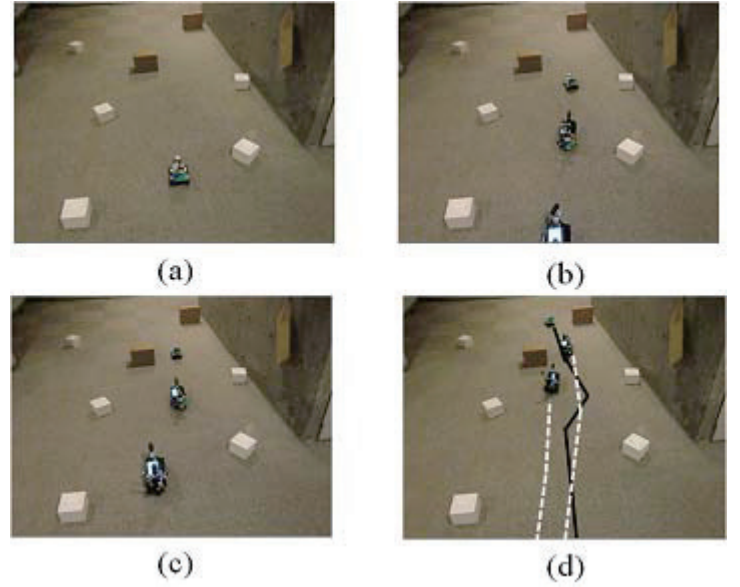


Figure 11. Appearance of line experiment

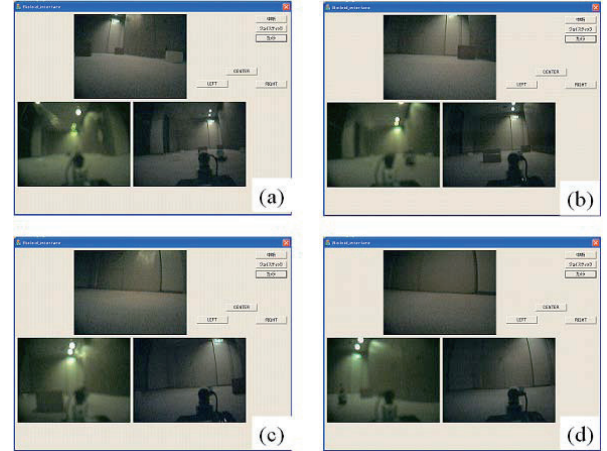


Figure 12. Images sent from robots in tandem formation behavior

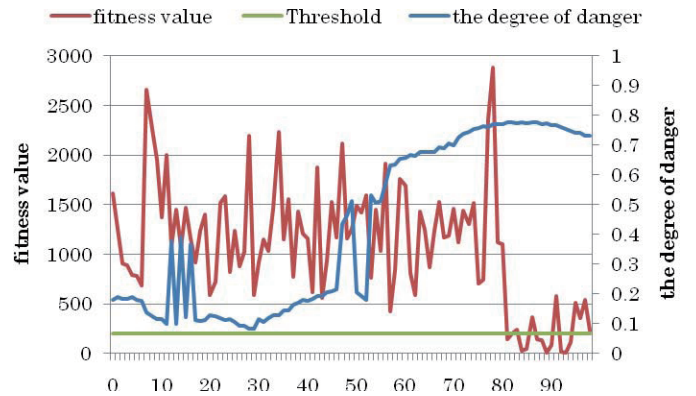


Figure 13. The change of fitness value and the degree of danger in the tandem formation behavior

Next, we show experimental results of a basic triangular formation behavior of three robots. Here we use 30 degree of relative angle to construct the shape of equilateral triangle. Figures 14 and 15 show overview of an experimental result of tele-operation and images sent from robots, respectively. In Figure 14 (d), the solid and dotted lines indicate the trajectories of the leader robot and follower robots, respectively. The follower robot traces the rear of the leader robot with suitable angle and distance. Figure 16 shows the change of fitness value and the degree of danger in the tandem formation behavior.

Figure 16 shows the change of fitness value and the degree of danger in the triangle formation behavior of second robot (Follower 1). In the experimental result, since the fitness value is larger than the threshold (200) for the target tracing, the robot successfully traces the rear of the leader robot. In this case the maximum fitness is not stable as in the tandem formation. Tandem formation always captured landmark at a front. However, triangle formation captured landmark at an angle. So the triangle formation's maximum fitness is unstable.

Finally, we compare the view areas expanded by the tandem formation behavior and basic triangular formation behavior. In case of tandem formation behavior, the image sent from the last follower robot includes the far but wide range surrounding the leader robot. On the other hand, in case of basic triangular formation behavior, the image sent from two follower robots can expand the view area of left and right sides, respectively, but these two images are not symmetrical from the position of the leader position. In this way, these two formation behaviors have one advantage and one disadvantage, respectively. In order to solve this problem, we are developing a 3D visualization method based on distance and color information.

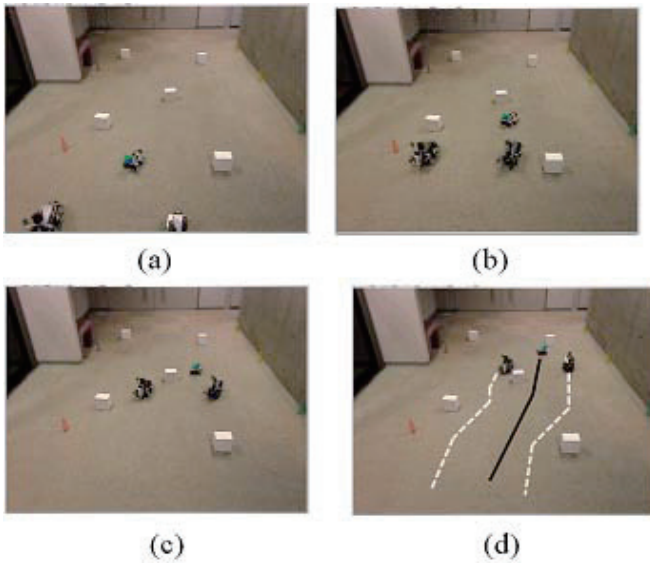


Figure 14. Appearance of line experiment

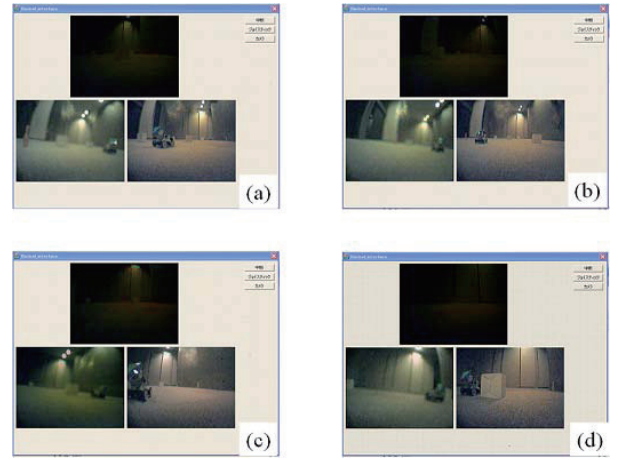


Figure 15. Leader's interface of triangle experiment

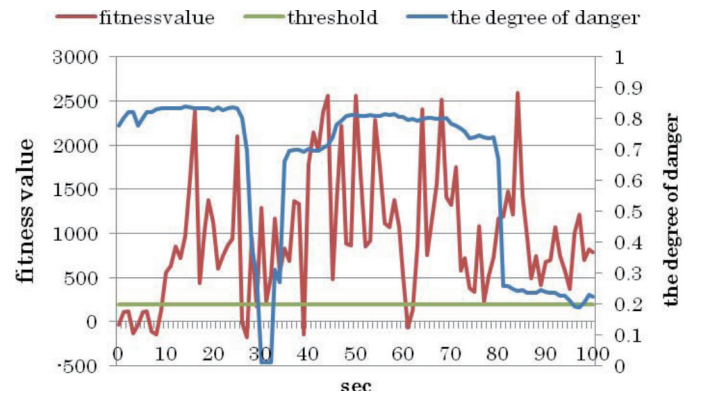


Figure 16. The change of fitness value and the degree of danger in the tandem formation behavior

V. SUMMARY

In this paper, we discussed the formation behavior of multi-robot based on sensor fusion under different environmental conditions. Furthermore, we proposed the method of image processing by a steady-state genetic algorithm for relative localization, and applied a multi-objective behavior coordination method based on fuzzy control. The experimental results showed the effectiveness of the proposed method for target tracing and collision avoidance of the Follower under the tele-operation of the Leader. However, the hybrid communication by wireless LAN, ZigBee, XBee, and Bluetooth is under development. We will propose a control method of several communication technologies. Furthermore, we discuss how to change or update the shape of a formation of three robots according to environmental conditions.

VI. REFERENCE

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