SICE Annual Conference 2007
Sept. 17-20, 2007, University of Fukui, Japan

Localization of Mobile Robots by Multiple Landmark Recognition

Ryohei Ozawa[1] Yasushi Mae[2] and Mamoru Minami[1]

[1]Graduate School of Engineering, University of Fukui, Fukui, Japan
(Tel : +81-776-27-8527;Email: {ozawa,minami}@rc.his.fukui-u.ac.jp)
[2]Graduate School of Engineering Science, Osaka University, Japan
(Tel : +81-6-6850-6366;E-mail: mae@sys.es.osaka-u.ac.jp

Abstract: The paper proposes a method for localization of mobile robots by multiple landmark recognition. Landmarks are recognized in real time by Model-based matching method using Genetic Algorithms (GA). A mobile robot measures directions of landmarks while moving. Target landmarks are changed depending on the situation of the robot. The individuals of GA are allocated for recognizing multiple landmarks efficiently depending on the situation. The robot estimates its position by the directions of the two landmarks and its moving distance. We perform experiments using a mobile robot in a RoboCup soccer field. In the experiment, goalposts and corner posts are used as landmarks. Experimental results show the effectiveness of the method.

Keywords: Localization, Resource Allocation, Visual Attention, Gazing-GA

1. INTRODUCTION

Localization is a basic and important task for mobile robots such as life-service robots in human-robot environments. Visual landmarks are used for localization in indoor service robots since GPS cannot be used in buildings and high precision localization is required for doing indoor service tasks such manipulation of daily objects. There are some methods of localization by visual landmark recognition [1], [2]. Localization in real time is useful for moving and manipulation smoothly. For real-time localization, the robot must recognize multiple landmarks quickly. Human vision, whose ability is beyond state-of-the-art robot vision, can recognize multiple objects at a time. Even human vision, however, has a limit number of simultaneous recognizable objects, since cognitive resource of human vision is limited. Robot and computer vision, as a matter of course, have a limit number of simultaneous recognizable objects, since computational resource for recognition is limited, too.

There is a well-known fact that humans move their eyes fast and change attentional objects for understanding a scene. In robot vision, there has been proposed a methodology, active vision [3], [4], [5], which realizes a function of selective attention. We consider these saccade and selective attention functions provide an ability of multiple object recognition to humans and robots. From the fact that the cognitive resource of human at an instant time is limited, we assume that humans recognize multiple objects in a scene by unconsciously integrating instantaneously acquired object information in a short time-series. We also assume that humans allocate cognitive resource for recognition of objects by paying attention to the objects according to the priority order which depend on situations.

In the present paper, we propose a method of localization of mobile robots by recognizing visual landmarks using real-time resources allocation of visual attention. In the proposed method, recognition process is performed by Model-based matching method using Genetic Algorithms (GA). Positions of object models are represented by individuals of GA. The total number of models determines the total cognitive resource. The numbers of searching models for different objects are changed according to the priority of the object recognition. The priority is determined based on the situation for localization. The robot estimates its position by the directions of the two recognized landmarks and its moving distance. Effectiveness of the method is ascertained by localization experiments in the RoboCup soccer field.

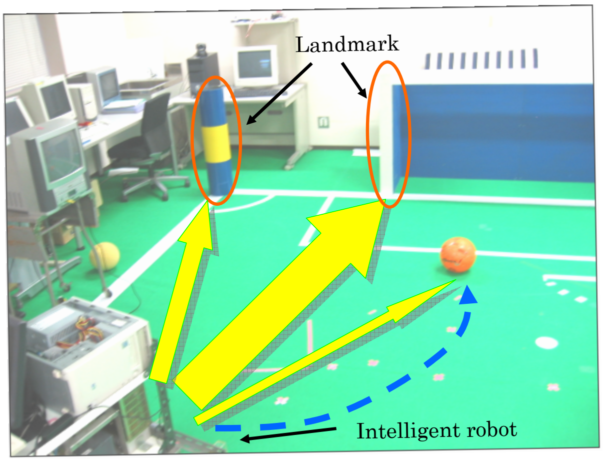

Fig. 1 Resource Allocation of Visual Attention for Localization of Mobile Robots

2. BASIC IDEA OF THE METHOD

In this section, we explain basic idea of the method. As the visual landmarks are recognized earlier, the robot can estimate its position earlier. By allocating resource of visual attention depending on the situation, the robot can recognize multiple landmarks for localization (See Fig.1). The thickness of the arrow in Fig.1 expresses the amount of visual attention. For localization in a soccer field, static objects such as goalposts and corner posts are

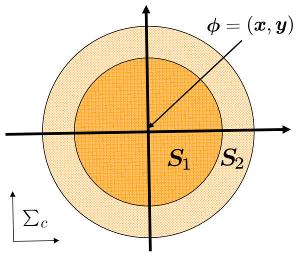

Fig. 2 Ball search model

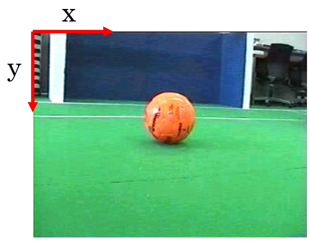

Fig. 3 Input image of ball search

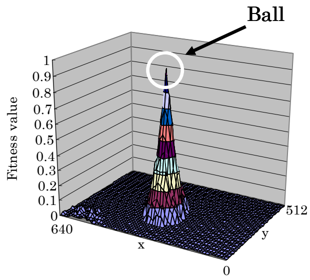

Fig. 4 Searching result by model of Fig.2

used as landmarks. Then the recognition resources are allocated more for recognizing goalposts and corner posts.

In the paper, the robot knows the absolute position of landmarks and the landmark models of visual patterns for recognizing the landmarks. The landmarks are recognized by Model-based matching method using GA. The individuals of the GA represents the positions of the searching models for a landmark. The population of the individuals is considered as the total resource of visual attention. The more individuals are used for a landmark, the landmark can be recognized earlier and more precise. By chaning the number of individuals for multiple landmarks depending on the situations, the multiple landmarks for localization are recognized earlier.

The robot estimates its position by the directions of the two recognized landmarks and its moving distance. The directions of the landmarks from the robot is obtained from the camera orientation and the image coordinate. The moving distance of the robot is obtained from the circular encoder of the motor.

3. RECOGNITION OF TARGET OBJECTS

3.1 Recognition by Model-based Matching

A target object is recognized by Model-based matching method. This is a method of evaluating the input image using a known geometric model, and detecting the position/orientation of the object. Shape of the target on the image, which includes derivation and integration of brightness and color distribution, is given as a model. We call it surface-strips model [6], [7], [8]. Fitness function, which evaluates the matching degree between the model and the object appearance on the image, can be calculated at every position.

The position/orientation of object are expressed by the position/orientation of the model, where fitness function is maximized. Finding the maximum of the fitness function changes the recognition problem into an optimization problem.

Target objects for recognition in our experimental setup are goalposts and corner posts. They have their specified own color determined by the rule of the RoboCup. These colors are used for calculating fitness function of each object. An example of the object model and the fitness function are described below.

3.1.1 Ball Model

We explain Model-based matching method by using ball recognition as an example. The ball used in RoboCup medium league is colored orange by regulation. In order to extract orange of the ball, the threshold of hue H is set. By preliminary experiments, orange can be specified by limiting the value of H to 7-35. The image domain obtained from camera is expressed as follows:

$$\Omega_{camera} = \{\boldsymbol{r} = (x, y) \mid 0 \le x \le x_{max} \ , \\ 0 \le y \le y_{max}\}. \qquad (1)$$

Then, a set of orange point Ω_{orange} is expressed by the following equation:

$$\Omega_{orange} = \{x, y \mid 7 < H(x, y) < 35\}, \qquad (2)$$

where, x_{max} and y_{max} shown in Eq.1 are positive constants, and also the limited values along the axes x and y of image coordinate. The evaluation function of orange is defined as

$$h_{orange}(\boldsymbol{r}) = \left\{ \begin{array}{c} 1(\boldsymbol{r} \in \Omega_{orange}) \\ 0(\boldsymbol{r} \notin \Omega_{orange}) \end{array} \right\}. \qquad (3)$$

In order to detect the ball from an input image, it is necessary to detect circular orange. Model-based matching method is used to detect the center position of the ball in input image. A searching model consists of two circles, $\boldsymbol{S}_1$(Orange domain) and $\boldsymbol{S}_2$(Orange domain) as shown in Fig.2. In the figures variables $\boldsymbol{\phi} = (\boldsymbol{x}, \boldsymbol{y})$ represents the center position of the model. Correlation with an input image and the searching model is defined as follows:

$$F_{Size}(\boldsymbol{\phi}) = \frac{\sum_{\boldsymbol{r} \in \boldsymbol{S}_1} h_o(\boldsymbol{r})}{\sum_{\boldsymbol{r} \in \boldsymbol{S}_1} \boldsymbol{r}} - \frac{\sum_{\boldsymbol{r} \in \boldsymbol{S}_2} h_o(\boldsymbol{r})}{\sum_{\boldsymbol{r} \in \boldsymbol{S}_2} \boldsymbol{r}} \qquad (4)$$

The filtering result by using Eq.4 with respect to the input image Fig.3 are shown in Fig.4 respectively. Each filtering result in Fig.4 have a peak corresponding to the position of the ball.

3.2 Recognition by GA

Moreover, in order to discover the maximum of the fitness function for a short time, without calculating the whole image like global searching methods, Genetic Algorithm(GA) is used. And, to realize the real-time processing and detect the target position from the consecutively input images, We have proposed a new idea of an evolutionary recognition process for dynamic image, in which the evolution of GA is applied only one time to the newly input image. We named it "Step-GA". Furthermore, in order to increase the tracking performance, we employ a hybrid-searching method, which is a localized search technique of GA combined with global GA process. We call it "Gazing GA".

3.3 Resource Allocation of Visual Attention

In this research, it is necessary to detect a landmark position earlier and more precisely for localization. We perform object recognition using resource allocation of visual attention in the following two cases.

In the first case, the number of searching models for a landmark is changed according to the fitness value of the landmark recognition.

In the second case, the number of searching models for different objects are changed according to the priority of the object recognition. The priority depends on the situation of the robot. Effectiveness of ''Resource Allocation of Visual Attention" has shown in [9].

3.3.1 Resource allocation depending on fitness of landmark

The number of searching models for a landmark is changed according to the fitness value of the landmark recognition. The fitness value represents the accuracy of object recognition. If the fitness value for a landmark recognition exceeds a threshold, the number of searching models for the landmark is increased so that the landmark can be recognized earlier. The max number of searching models will henceforth be written as P_{max} for simplicity. And, the threshold value for judging whether the subject was detected will be written F_{min}. When fitness of a landmark exceeds F_{min}, the numbers of searching models for the landmark becomes P_{max}. And the number of searching models for other landmarks becomes 0.

We performed two experiments of landmark recognition. Left goalpost is used as landmark for recognition. P_{max} was set up with 30, and F_{min} was set up with 0.4. After starting landmark search, the number of searching models for left corner post was 10. First, change of fitness with cognitive resource allocation and wihtout allocation are shown in Fig.5. We can see that increase of fitness with allocation is more faster than without allocation after exceeding F_{min}. Second, we examined the number of times of GA-evolution after fitness exceeds F_{min} until it becomes 0.7 or more. The experiment was performed 100 times respectively. The average of the numbers of evolution times with allocation and without allocation are shown in Table1. We can see that the average with allocation is 4.44 times, and without allocation is 8.83 times. Landmarks can be recognized more faster when using cognitive resource allocation.

3.3.2 Resource allocation depending on situation of robot

In this section, we perform the method that the number of searching models for different objects are changed according to the priority of the object recognition. In general, subject recognition accuracy improves so that many resources are used. We examined the number of times of GA-evolution until fitness exceeds 0.7. Left goalpost is used for recognition. The experiment was performed 100 times. The avarage of the number of evolution times is shown in Fig.6. We can see the number of evolution times is decreased by increasing search resources. We will explain the priority of the object recognition in chapter 5.3.

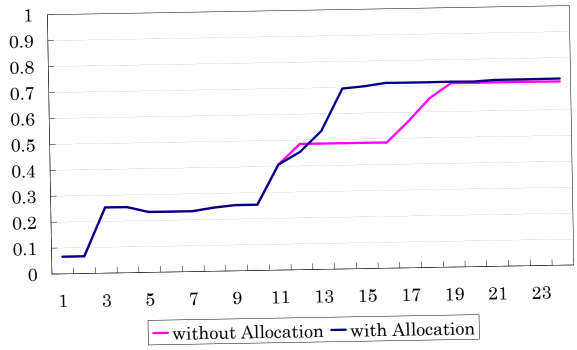

Fig. 5 Change of Fitness with Allocation

Table 1 Change of Fitness with Allocation

	with Allocation	without Allocation
Ave. of Evolution Times	4.44	8.83

4. LOCALIZATION OF THE ROBOT

All the cases of positional relation of a robot and two landmarks are classified into three cases shown in Fig.7,Fig.8,Fig.9. The robot estimates its position (A-D) by the trianglation using the directions of the two landmarks (θ_1-θ_4) and its moving distance(m_1-m_3). We explain the process of obtaining a parameter (m_1,m_2,m_3,θ_1,θ_2,θ_3) required for calculation of localization by using Fig.7,Fig.8,Fig.9. The representation of process can be seen as follows.

1. When the robot recognizes a landmark, the robot estimates the direction of a landmark (θ_1) from the angle of the camera at A.
2. The robot moves some distance(m_1).
3. The robot estimates once again the direction of the

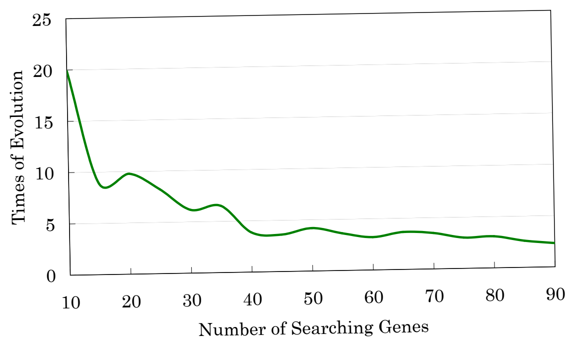

Fig. 6 Fitness with Allocation

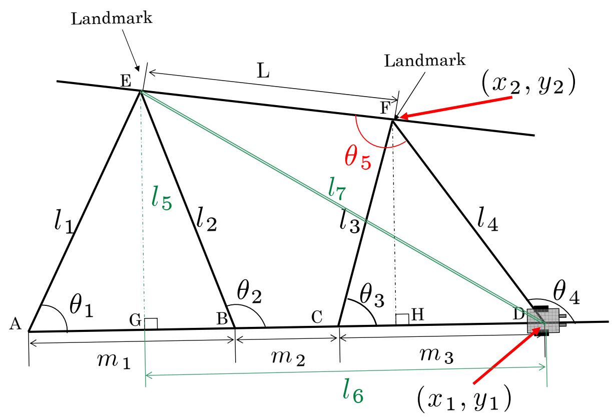

Fig. 7 Self-Localization Using Triangulation Pattern1

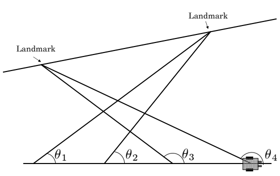

Fig. 8 Pattern2

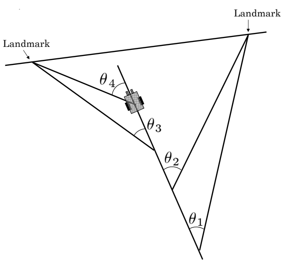

Fig. 9 Pattern3

same landmark with process (1.)(θ_2) at B.

4. The robot moves some distance(m_2).
5. The robot estimates the directions of difference landmark(θ_3,θ_4) and moving distance(m_3) by the same process (1.2.3.) at C and D.

4.1 Calculational Method of Localization

Robot positions A, B, C, D are calculated by using parameter (m_1,m_2,m_3,θ_1,θ_2,θ_3) . In this section, we explain the detail of calculation in the case of Fig.7.

Equations for calculating position D is shown by follows.

The distance from A and B to the landmark E are measured by triangulation for triangle ABE as follows.

$$l_1 cos\theta_1 - l_2 cos\theta_2 = m_1 \tag{5}$$

$$l_1 sin\theta_1 = l_2 sin\theta_2 \tag{6}$$

$$l_1 = \frac{sin\theta_2}{sin\theta_1} l_2 \tag{7}$$

From eq.(5) and eq.(7), we obtain

$$\begin{aligned} l_2 &= \frac{m_1}{(\frac{sin\theta_2 cos\theta_1}{sin\theta_1} - cos\theta_2)} \\ &= \frac{m_1 sin\theta_1}{sin\theta_2 cos\theta_1 - cos\theta_2 sin\theta_1} \\ &= \frac{m_1 sin\theta_1}{sin(\theta_2 - \theta_1)} \end{aligned} \tag{8}$$

(9)

By substituting eq.(4) to eq.(3), we obtain

$$l_1 = \frac{m_1 sin\theta_2}{sin(\theta_2 - \theta_1)} \tag{10}$$

(11)

l_3, l_4 are obtained in the same way for triangle CDF .

Then, we obtain

$$l_5 = l_1 sin\theta_1 \tag{12}$$

$$l_6 = m_2 + m_3 - l_2 cos\theta_2 \tag{13}$$

For triangle GDE, Eq.(12) and Eq.(13) yield

$$l_7 = \sqrt{l_5^2 + l_6^2} \tag{14}$$

For triangle DEF, l_4, l_7 and L yield

$$cos\theta_5 = \frac{L^2 + l_4^2 - l_7^2}{2Ll_4} \tag{15}$$

$$\theta_5 = arcos(cos\theta_5) \tag{16}$$

The robot position at D is obtained by using l_4, θ_5 and absolute coordinate of landmark at F, as follows.

$$x_1 = x_2 - l_4 cos\theta_5 \tag{17}$$

$$y_1 = y_2 - l_4 sin\theta_5 \tag{18}$$

5. LOCALIZATION EXPERIMENTS

We perform experiments using a mobile robot in a RoboCup soccer field. P_{max}, that is the max number of sarching genes was set up with 30. F_{min} for goalposts was set up with 0.5 and F_{min} for corner posts was 0.6. Environment of experiment is shown in Fig.10. In the experiment, goalposts and corner posts are used as landmarks. The robot recognized the left corner post at 1 and 2 , and theb left goalpost at 3 and 4.

The moving distance between 1 and 2, and the moving distance between 3 and 4 are limited 0.5m or more in order to maintain localization accuracy. And, movement speed of the robot was made into 2.1 cm/s. We perform two experiments of localization. One is localization with cognitive resource allocation. Another is localization without cognitive resource allocation. The corner posts, the left-goalpost and the right-goalpost will henceforth be written as CP, LGP and RGP, for simplicity.

5.1 Landmarks Recognition

5.1.1 Goalpost Recognition

In order to detect the goalpost from an input image, it is necessary to detect edge of a goalpost. The goalpost used in this experiment is colored white, and inside of the goal is blue. A searching model consists of three boxes, $\boldsymbol{S}_1$(White domain), $\boldsymbol{S}_2$(Blue domain) and $\boldsymbol{S}_3$(Blue domain) as shown in Fig.12.

Where, blue can be specified by limiting the value of H to 200-220. A set of blue point Ω_{blue} is expressed by the following equation:

$$\Omega_{blue} = \{x, y \mid 200 < H(x, y) < 220\}, \tag{19}$$

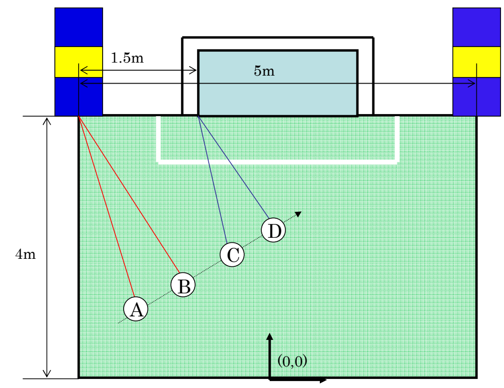

Fig. 10 Soccer Field

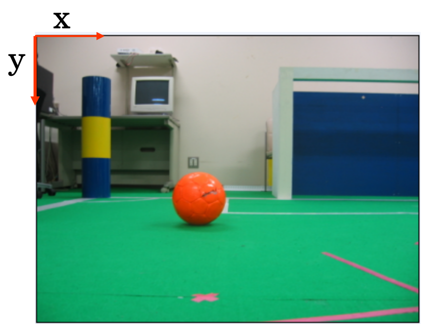

Fig. 11 Input image for recognition

The evaluation function of blue is defined as

$$h_{blue}(\mathrm{r}) = \left\{ \begin{array}{l} 1(\mathrm{r} \in \Omega_{blue}) \\ 0(\mathrm{r} \notin \Omega_{blue}) \end{array} \right\} \tag{20}$$

One part of correlation with an input image and the searching model is defined as follows:

$$h_{blue}(\boldsymbol{\phi}) = \frac{\sum_{\boldsymbol{r}\in\boldsymbol{S}_2} h_b(\boldsymbol{r})}{\sum_{\boldsymbol{r}\in\boldsymbol{S}_2} \boldsymbol{r}} - \frac{\sum_{\boldsymbol{r}\in\boldsymbol{S}_3} h_b(\boldsymbol{r})}{\sum_{\boldsymbol{r}\in\boldsymbol{S}_3} \boldsymbol{r}} \tag{21}$$

White don't have hue (H). Fitness function of white is defined as the difference of brightness between a goalpost (White domain) and inside of goal (Blue domain). The brightness of goalpost is defined as $b_w(r)$, and the brightness of inside of goal is defined as $b_b(r)$. From $b_w(r)$ and $b_b(r)$, we obtain

$$b_{white}(\boldsymbol{\phi}) = \frac{\sum_{\boldsymbol{r}\in\boldsymbol{S}_1} b_w(\boldsymbol{r})}{\sum_{\boldsymbol{r}\in\boldsymbol{S}_1} \boldsymbol{r}} - \frac{\sum_{\boldsymbol{r}\in\boldsymbol{S}_2} b_b(\boldsymbol{r})}{\sum_{\boldsymbol{r}\in\boldsymbol{S}_2} \boldsymbol{r}} \tag{22}$$

$b_{white}(\boldsymbol{\phi})$ of best position is about 0.3. In order to set maximum of fitness to 1, correlation with an input image and the searching model is defined as follows:

$$F_{goalpost}(\boldsymbol{\phi}) = \frac{2}{3} h_{blue}(\boldsymbol{\phi}) + b_{white}(\boldsymbol{\phi}) \tag{23}$$

The filtering result by using Eq.23 with respect to the input image Fig.11 are shown in Fig.14 respectively. Each filtering result in Fig.14 have a peak corresponding to the position of the goalpost.

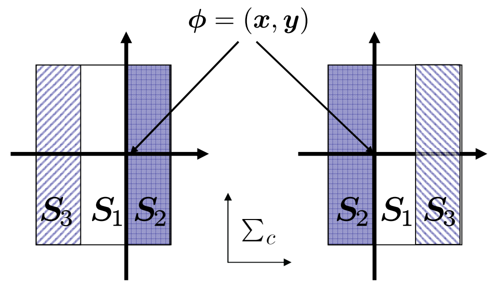

Fig. 12 Goalpost search model (left and right)

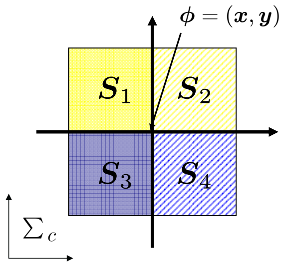

Fig. 13 Corner post search model

5.1.2 Corner Post Recognition

In order to detect the corner post from an input image, it is necessary to detect edge of the corner post. The goalpost used in this experiment is colored blue and yellow. A searching model consists of three boxes, $\boldsymbol{S}_1$(Yellow domain), $\boldsymbol{S}_2$(Yellow domain), $\boldsymbol{S}_3$(Blue domain) and $\boldsymbol{S}_4$(Blue domain). as shown in Fig.13

Where, yellow can be specified by limiting the value of H to 45-60. A set of yellow point Ω_{yellow} is expressed by the following equation:

$$\Omega_{yellow} = \{x, y \mid 45 < H(x,y) < 60\} \tag{24}$$

The evaluation function of yellow is defined as

$$h_{yellow}(\mathrm{r}) = \left\{ \begin{array}{l} 1(\mathrm{r} \in \Omega_{yellow}) \\ 0(\mathrm{r} \notin \Omega_{yellow}) \end{array} \right\} \tag{25}$$

Correlation with an input image and the searching model is defined as follows:

$$F_{cp}(\boldsymbol{\phi}) = ((\sum_{\boldsymbol{r}\in\boldsymbol{S}_1} h_{yellow}(\boldsymbol{r}) - \sum_{\boldsymbol{r}\in\boldsymbol{S}_2} h_{yellow}(\boldsymbol{r})) + (\sum_{\boldsymbol{r}\in\boldsymbol{S}_3} h_{blue}(\boldsymbol{r}) - \sum_{\boldsymbol{r}\in\boldsymbol{S}_4} h_{blue}(\boldsymbol{r})))/2 \tag{26}$$

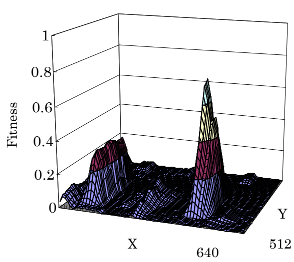

Fig. 14 Searching result by model of Fig.12

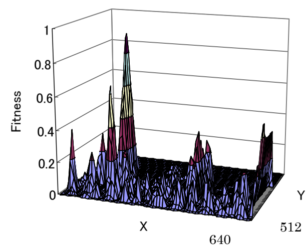

Fig. 15 Searching result by model of Fig.13

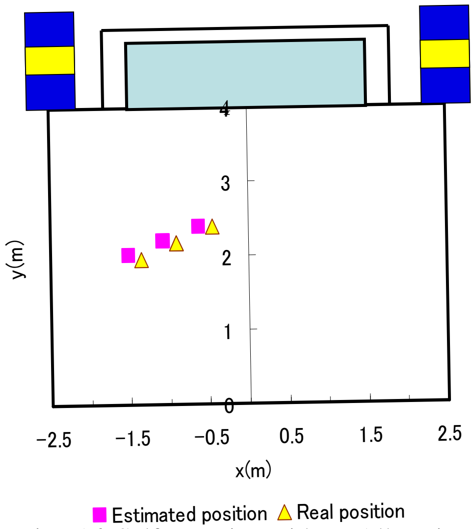

Fig. 16 Self-Location without Allocation

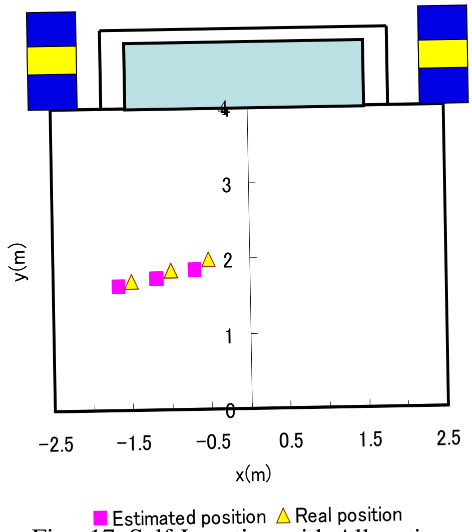

Fig. 17 Self-Location with Allocation

Table 2 Measurement Result(without Allocation)

	θ_1(deg)	θ_2	θ_3	θ_4	m_1(m)	m_2	m_3
para	-91.54	-104.19	-66.14	-82.33	0.502	0.008	0.505

Table 4 Measurement Result(with Allocation)

	θ_1(deg)	θ_2	θ_3	θ_4	m_1(m)	m_2	m_3
para	-96.98	-107.91	-74.11	-86.86	0.501	0.007	0.502

Table 3 Position and Error(without Allocation)

	A	B	C	D	average
real x(m)	-1.35	-0.91	-0.91	-0.45	-
real y(m)	1.95	2.17	2.17	2.39	-
x(m)	-1.51	-1.08	-1.07	-0.63	-
y(m)	2.01	2.20	2.21	2.39	-
Error(m)	0.17	0.17	0.17	0.18	0.17

Table 5 Position and Error(with Allocation)

	A	B	C	D	average
real x(m)	-1.50	-1.00	-1.00	-0.52	-
real y(m)	1.70	1.85	1.85	1.99	-
x(m)	-1.66	-1.18	-1.17	-0.69	-
y(m)	1.63	1.73	1.73	1.84	-
Error(m)	0.17	0.22	0.22	0.23	0.21

The filtering result by using Eq.26 with respect to the input image Fig.11 are shown in Fig.14 respectively. Each filtering result in Fig.15 have a peak corresponding to the position of the goalpost.

5.2 Localization without allocation

We perform experiments of localization without cognitive resource allocation. The number of individuals for landmarks are set 10,10,10 for CP,LGP,RGP, respectively.

Estimated parameter (θ_1-θ_4, m_1-m_3) are shown in Table2. The position errors are shown in Table3. And, we can show comparison of positions in Fig.16. In this figure, positions of localization are compared with real positions. We can see that the effectiveness of the method and the average of position errors is 17cm.

5.3 Localization with allocation

We perform experiments of localization without cognitive resource allocation. Change of each number of searching models is shown as follows :

1. The robot searches a landmark. (CP,LGP,RGP)=(10,10,10)
2. The number of CP-models increase after judging CP exists in a screen. (CP,LGP,RGP)=(30,0,0)
3. After direction of left-CP is estimated twice, the robot must search a landmark other than left-CP (LGP, RGP, right-CP). Therefore, the total genes are allocated equally again. (CP,LGP,RGP)=(10,10,10)
4. The number of LGP-genes increase after judging LGP exists in a screen. (CP,LGP,RGP)=(0,30,0)

Estimated parameter (θ_1-θ_4, m_1-m_3) are shown in Table4. The position errors are shown in Table5. And, we can show comparison of positions in Fig.17. In this figure, positions of localization are compared with real positions. We can see that the effectiveness of the method and the average of position errors is 21cm.

5.4 Effectiveness of Allocation

Effectiveness of Allocation is shown by m_1, m_2 and m_3 in Table2 and Table4. Time after starting search until the robot discovers a landmark depend on m_1-m_3. m_1 and m_3 are limited 0.5m or more. Therefore, moving distance after starting search until the robot discovers a landmark are shown in Table6.

Table 6 Moving Distance

	m_1(mm)	m_2	m_3	SUM
with Allo.	1.0	0.7	2.0	3.7
without Allo.	2.0	0.8	5.0	7.8

6. CONCLUSION

In this paper, we proposed the method of localization for mobile robots with pan-tilt camera by multiple landmark recognition. In this research, it is necessary to detect a landmark position earlier and more precisely for localization. Thus, we perform landmarks recognition in real time using resource allocation of visual attention. Landmarks are recognized by Model-based matching method using Genetic Algorithms (GA). Positions of object models are represented by the individuals of GA. Moreover, the individuals of GA are allocated for recognizing multiple landmarks efficiently depending on the situation. We performed experiments using a mobile robot in a RoboCup soccer field. In the experiment, goalposts and corner posts were used as landmarks. Experimental results showed the effectiveness of the method.

REFERENCES

[1] K.Komoriya, E.Oyama, and K.Tani ''Planning of Landmark Measurement for the Navigation of a Mobile Robot" IEEE International Conference on Intelligent Robot and Systems, pp.1476-1481, 1992

[2] K.T.Sutherland, W.B.Thompson ''Localization in Unstructured Environment: Dealing with the Errors", IEEE International Conference on Robotics and Automation, pp.740-754, 1994.

[3] Y. Aloimonos and I. Weiss, "Active Vision," International Journal of Computer Vision, vol.1, no.4, pp.333-356, 1988.

[4] R. Bajcsy, "Active Perception," IEEE Proceedings, vol.76, no.8, pp.996-1006, 1988.

[5] D.H. Ballard and C.M. Brown, "Principles of animate vision," In Y.Aloimonos (ed.), Active Perception, Lawrence Erlbaum Association, Publishers, pp.245-282, 1993.

[6] M.Minami, H.Suzuki, M.Miura, "Real-Time Robust Recognition of Human using Illuminance-depending Gazing GA," Proc. Knowledge-Based Intelligent Information Engineering Systems and Allied Technologies, pp.1377-1382, 2002.

[7] M.Minami, J.Agbanhan and T.Asakura, "Manipulator Visual Servoing and Tracking of Fish Using Genetic Algorithm," International Journal of Industrial Robot, vol.29, no.4, pp.278-289, 1999.

[8] M.Minami, J.Agbanhan and T.Asakura, "A Method of Model-Based Object Recognition," Japan/USA Symposium on Flexible Automation, vol.2, pp.905-912, 1996.

[9] M.Minami, Y.Mae, W.song and T.Mizushima ''Generation of Adaptive MotionUsing Quasi-simultaneous Recognition of Plural Targets",ICCAS(2005)CD-ROM 882-887.