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Paper:

Vision-Based Object Tracking by Multi-Robots

Takayuki Umeda, Kosuke Sekiyama, and Toshio Fukuda

Department of Micro System Engineering, Nagoya University
1 Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan
E-mail: {umeda, sekiyama, fukuda}@robo.mein.nagoya-u.ac.jp
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This paper proposes a cooperative visual object tracking by a multi-robot system, where robust cognitive sharing is essential between robots. Robots identify the object of interest by using various types of information in the image recognition field. However, the most effective type of information for recognizing an object accurately is the difference between the object and its surrounding environment. Therefore we propose two evaluation criteria, called ambiguity and stationarity, in order to select the best information. Although robots attempt to select the best available feature for recognition, it will lead a failure of recognition if the background scene contains very similar features with the object of concern. To solve this problem, we introduce a scheme that robots share the relation between the landmarks and the object of interest where landmark information is generated autonomously. The experimental results show the effectiveness of the proposed multi-robot cognitive sharing.

Keywords: object tracking, multi-robot, feature evaluation, feature selection, autonomous landmark generation

1. Introduction

Many projects that include cooperative distributed tasks using multi-robots are underway. Above all, improving the visual-cognitive ability of robot is important to make the system adaptable to the actual environment. Therefore, we discuss two cognitive-ability factors required for multi-robot systems. The first is the ability of a robot to recognize an object accurately. The second is cognitive sharing, which is a typical issue in multi-robot systems. Cognitive sharing involves identifying the object or event and sharing them with the other robots. As regards object recognition, many methods have been proposed before. The method described in [1] uses a color histogram and that described in [2] uses a histogram of texture as a feature used for recognizing similar objects. These methods are efficient when it comes to single-color objects or objects with simple texture, but they cannot be used for complex objects. Meanwhile, many methods that focus on local features have been suggested. The method described in [3] uses the Harris interest point operator, while those described in [4] and [5, 6] use an original interest-point-detection algorithm to extract local area information and relate it to the occlusions. On the other hand, [7] discusses the recognition of more kinds of object by describing the probabilistic model of the local area and the positional relation. However, these methods based on local features will depress the cognitive ability because they cannot extract enough interesting points with respect to a simple object, whereas this ability is high in [1] and [2]. Furthermore, in distributed robots system [8, 9], robots are observing objects from different field of view. So the effectiveness of the features proposed in conventional work depends on the representation of objects as well as their surrounding environment. So the effectiveness of the features that have been proposed before depends on objects that should be recognized as well as their surrounding environment. Thus, in this paper, we propose evaluation parameters such as ambiguity and stationarity to assess the effectiveness of each feature described in full detail in Section 2. Depending on the object that should be recognized and the surrounding environment, we try to solve this problem by selecting a feature that presents a small probability of false recognition based on these evaluation parameters. Next, we discuss cognitive sharing. In the previous studies on multi-robot cooperative tasks, Tan [10] and LeBlanc [11] simplified the cognitive sharing by using a RFID tag on the target whose information needs to be shared and Xue [12] simplified by using QR-code. Also, in situations where environment information is limited, such as at the RoboCup, specific objects like the goal are treated as landmarks and cognitive sharing is handled by utilizing the relation between those landmarks and the ball [13]. But to invest in using multi-robot systems in the human society or in extreme environments, we cannot use markers because the information of the target that needs to be shared will change dynamically according to the task. Also, in an unknown environment, it is difficult to configure the landmark preliminarily. Therefore, in this paper, we try to solve this problem by identifying the target based on the landmark that the robot determined autonomously. We use as landmark an object that can be easily identified and shared; in other words, a unique object that presents a small probability of false recognition. Here, based on the aforementioned feature-selection method, the robot will select the most efficient feature with respect to each object that it is recognizing. Comparing the evaluation parameters of the selected feature, we can figure out the object, which is now easy to recognize. The most easily recognizable object is used as a landmark by the robot; we call this "landmark generation." In related research described in [14], planar quadrangulars like doors or posters that exist in the environment are treated as landmarks and are used for performing the environment mapping. Frintrop [15] proposed the landmark generation method which is focused on the SIFT detector and succeeded in visual localization and scene recognition. In this paper, first we define the ambiguity and stationarity as evaluation parameters for the color and shape feature; subsequently we consider their adequateness. Then we propose feature-selection and autonomous landmark-generation methods based on the evaluation values. Finally we indicate the effectiveness of our proposed methods by accomplishing cognitive sharing through cooperative object tracking.

2. Evaluation of Feature Effectiveness

2.1. Ambiguity and Stationarity Definition

In this section, we define ambiguity and stationarity, which are used to evaluate the effectiveness of the color and shape feature. Ambiguity is an indicator that is used to evaluate how ambiguous the feature is. For example, when the robot tries to recognize a blue ball among many blue-colored objects, it cannot identify which object the target is, based on the color feature. Therefore if there is no ambiguity in the situation – in other words the ambiguity of the feature has a low value – the feature is effective for recognizing the object accurately. Stationarity is an indicator that is used to evaluate the change rate of the ambiguity. The ambiguity changes according to the movement of the robot and the changes in the surrounding environment. Therefore if the change rate of the ambiguity is low, the feature is invariant with respect to environmental changes and is effective.

2.2. Ambiguity of Color Feature

2.2.1. Definition

First of all, we evaluate how a same-color object used as target is distributed in an input image by using a color histogram. Normalizing the target-color histogram H_{target} and the whole image's color histogram H_{image}, we calculate the intersection C of the two histograms by Eq. (1), and C can get a value between 0 and 1. i is the histogram's bin. If there are objects of the same color in the input image, C increases.

$$C = \sum_i \min(H_{target}(i), H_{image}(i)) \quad \ldots \ldots \quad (1)$$

The mean-shift tracker calculates the distribution of the histograms in the window and the center of gravity of the distribution. Then tracker transfers the window's center of gravity to the calculated distribution's one. Because the tracker searches for objects around the window, if objects

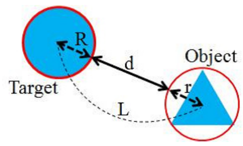

Fig. 1. Definition of the distance between objects.

of the same color as the target are present, the tracker will falsely recognize them. Therefore it is necessary to evaluate the distance between the target and the same-color objects. To evaluate the distance, we use a poisson distribution. The poisson distribution shown in Eq. (2) gives the probability distribution only based on the expected value of occurrences λ. And k refers to the number of occurrences of an event.

$$P_{(k)} = \frac{e^{-\lambda}\lambda^k}{k!} \quad \ldots \ldots \quad (2)$$

First, we define the distance between the target and other objects according to the following list and **Fig. 1**.

- Area of target: A_{target}
- Radius of target approximated by a circle: $R = \sqrt{A_{target}/\pi}$
- Same-color object's area: A_{object}
- Radius of object approximated by a circle: $r = \sqrt{A_{object}/\pi}$
- Distance between the center of the target and the object approximated by a circle: L
- Distance: $d = L - r - R$

Next, we define the distance as k.

$$d < 5 : k = 1$$
$$5 \cdot (n-1) \leq d < 10 \cdot n : k = n \quad (2 \leq n \leq 19)$$
$$95 \leq d : k = 20$$

If k is a small number, the distance is short and there is a high probability of false recognition. Then we can evaluate the distance by calculating the cumulative probability in $k < 6$, as shown in Eq. (3).

$$P = \int_0^5 P_{(k)} dk \quad \ldots \ldots \quad (3)$$

Finally we define the ambiguity in the color feature A_{color} by calculating the weighted geometric mean of C and P, because it depends highly on the distance between objects whether the false recognition happens or not. The ambiguity ranges from 0 to 1.

$$A_{color} = C^{\frac{n}{n+m}} \cdot P^{\frac{m}{n+m}} \text{ , } n : m = 1 : 3 \quad \ldots \ldots \quad (4)$$

2.2.2. Evaluation

In this section, we examine the correlation between the ambiguity found and the actual recognition rate. We evaluated the recognition performance of designated targets

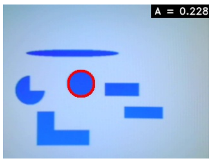

Fig. 2. Successful case in ideal scene.

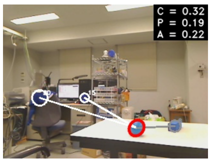

Fig. 3. Successful case in real scene.

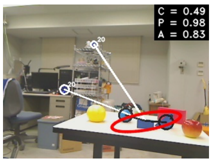

Fig. 4. Failure case in real scene.

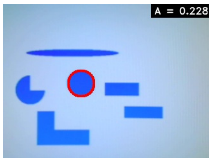

Fig. 7. Successful case in ideal scene.

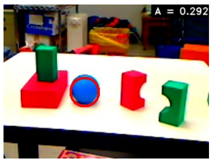

Fig. 8. Successful case in real scene.

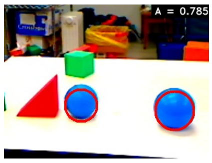

Fig. 9. Failure case in real scene.

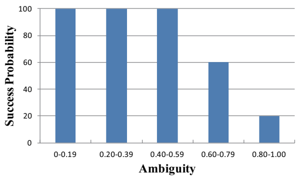

Fig. 5. Success prob. in ideal scene.

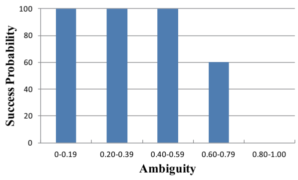

Fig. 6. Success prob. in real scene.

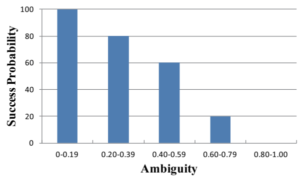

Fig. 10. Success prob. in ideal scene.

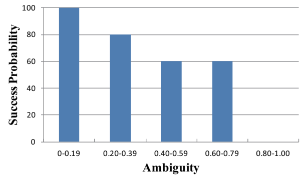

Fig. 11. Success prob. in real scene.

for 50 scenes in total. The breakdown is: 5 ideal and real scenes for each ambiguity value that is from 0.00 to 0.19, 0.20 to 0.39, 0.4 to −0.59, 0.6 to 0.79, and over 0.80. **Figs. 2**, **3**, and **4** are snapshots from the experiments. The target to recognize is a blue ball, the red circle corresponds to the recognition of an object by a robot, and the gray circles correspond to an approximated circle of other objects of the same color. In **Figs. 2** and **3**, the color distribution C is low, and P is low because the distances between objects d are long, thus A_{color} is low and the robot can recognize the target. However, in **Fig. 4**, C is similar to **Figs. 2** and **3**, P is high because there are blue objects near the target and each d is low. Thus A_{color} is high and the robot fails to recognize the target. We conducted experiments like the above for each ambiguity, and the results are shown in **Figs. 5** and **6**. The horizontal axis represents the ambiguity and the vertical axis represents the probability of success of the recognition, whose max value is 5. From these results, it is obvious that false recognition occurs when the ambiguity exceeds 0.60 and the robot cannot recognize the target based on the color feature when the ambiguity exceeds 0.80.

2.3. Ambiguity in the Shape Feature

2.3.1. Definition

We use a pattern-matching algorithm for the recognition of a target based on the contour feature. The similarity S_i of each contour is defined by Eq. (4) using the Hu moment h_k [16]. The additional character t refers to the target and i refers to each contour.

$$m_k^t = sign(h_k^t) \cdot \log | h_k^t |$$
$$m_k^i = sign(h_k^i) \cdot \log | h_k^i |$$
$$S_i = \sum_{k=1}^{7} | m_k^t - m_k^i | \quad \ldots \ldots \ldots \ldots \quad (5)$$

$S_i = 0$ means that the two contours match perfectly, whereas if S_i is high, they do not match. Therefore transforming S_i to S_i' by using the sigmoid function shown in Eq. (5), $S_i' = 1$ means perfect matching and is suitable for the meaning of the ambiguity.

$$S_i' = \frac{1}{1 + \exp^{-\alpha(S-\beta)}} \quad \ldots \ldots \ldots \ldots \quad (6)$$
$$\alpha = -15 \ , \ \beta = 0.3$$

By calculating S_i' for all contours obtained from the input image and the number of contours N, we can define the ambiguity on contour $A_{contour}$ based on Eq. (6). The ambiguity is found to be from 0 to 1.

$$A_{contour} = \frac{1}{N} \sum_{i=1}^{N} S_i' \quad \ldots \ldots \ldots \ldots \quad (7)$$

However, if there is no contour similar to the target, thus there is no contour with a S' over the threshold or if the robot cannot get the contour at all from the input image, the robot cannot recognize the target at all based on the contour feature and it sets the ambiguity value to $A_{contour} = 1$.

2.3.2. Evaluation

In this section, we examine the correlation between the ambiguity found and the actual recognition rate in the same way as for the color feature. **Figs. 7**, **8**, and **9** are snapshots from the experiments. In **Figs. 7** and **8**, $A_{contour}$ is low and the robot recognizes the target correctly. However, in **Fig. 9**, $A_{contour}$ is high and the robot fails to recognize target. We performed experiments similar to the above for each ambiguity, and the obtained results are shown in **Figs. 10** and **11**. Although false recognition occurs when the ambiguity exceeds 0.60 in the color feature, from these results it is obvious that false recognition occurs when the ambiguity exceeds 0.40 and the robot cannot recognize the target based on the contour feature when it exceeds 0.60.

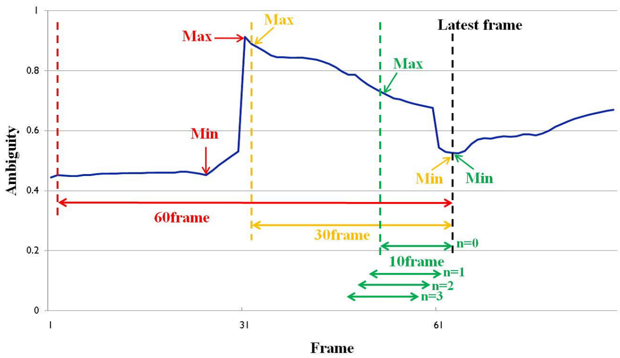

Fig. 12. Explanation drawing of stationarity.

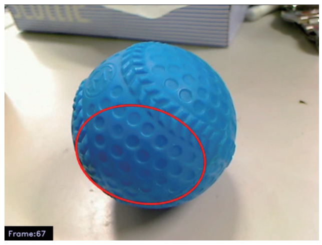

Fig. 13. Low-ambiguity scene. **Fig. 14.** High-ambiguity scene.

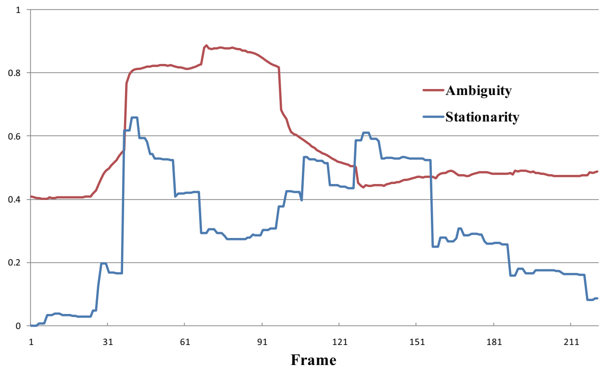

Fig. 15. Transition of ambiguity and stationarity.

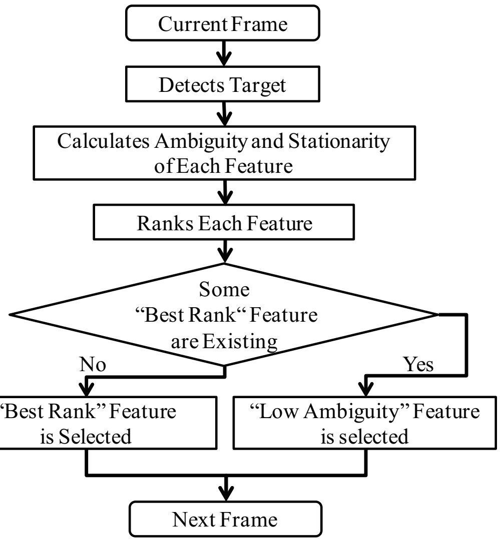

Fig. 16. Flowchart of feature selection.

2.4. Stationarity

2.4.1. Definition

In this section, we define stationarity. The drawing of **Fig. 12** can be used to explain this parameter. First, we calculate the difference between the maximum and the minimum value of the ambiguity in frame interval i based on Eq. (8). n denotes how many times ago the difference was calculated, with the latest frame interval being $n = 0$. Next, we sum the exponentially weighted $diff_n{}^i$ based on Eq. (9). Then we sum St_i weighted by w_i based on Eq. (10). The smaller the value of St is, the better. In addition, we discuss how to determine the frame intervals. These intervals are determined based on the movement velocity of the robots and the tracking object, and the fps of robot vision. In the experiment described in this paper, the tracking target crosses the field of view of the robot within 1 to 2 seconds. Consequently robots repeat their rotation and movement every 1 to 2 seconds when they are tracking the target. The fps of robot vision is about 10 to 30. Therefore, we estimate that we need to measure stationarity for up to 2 seconds and we decide that the frame intervals are 60 frames, 30 frames, 10 frames.

$$diff^i_n = Ambiguity_{\max} - Ambiguity_{\min} \quad \ldots \quad (8)$$

$$st_i = \sum_{n=0} diff^i_t \cdot \exp^{-n} \quad \ldots \quad (9)$$

$$S_t = \sum_{i}^{3} s_i \cdot w_i, \ (w_1 : w_2 : w_3 = 1:1:1) \quad \ldots \quad (10)$$

2.4.2. Evaluation

In this section, we examine the adequateness of stationarity using ambiguity with respect to blue color. In this experiment, we move the camera from the low-ambiguity scene shown in **Fig. 13** to the high-ambiguity scene shown in **Fig. 14**, and then return the camera to the scene shown in **Fig. 13**. We show the transition of ambiguity and stationarity calculated in the experiment in **Fig. 15**. From frame 1 to 25, the ambiguity remains nearly constant and the stationarity is less than 0.1. Then from frame 26 to 40, the ambiguity increases rapidly and the stationarity is over 0.6. After that, from frame 41 to 97, the change of the ambiguity is small and the stationarity starts to decrease slowly. From frame 98 to 132, the ambiguity decreases rapidly and the stationarity is over 0.6 again. Finally, after frame 132, the ambiguity remains nearly constant and the stationarity decreases. Based on this experiment, we confirmed that the stationarity works well when changes in ambiguity occur.

3. Feature Selection

In this section, we demonstrate the feature-selection method. **Fig. 16** shows the feature-selection flowchart. First, the robots calculate the ambiguity and the stationarity of the color and shape feature in every frame. Then the robots determine the rank of each feature based on the

Table 1. Feature evaluation.

Ambiguity	Stationarity	Rank
Low (≤ 0.5)	Low (≤ 0.5)	1
Low	High (> 0.5)	2
High (> 0.5)	Low	3
High	High	4

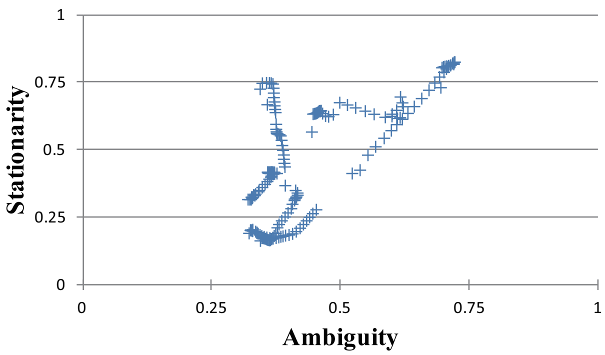

Fig. 17. Evaluation of object recognition based on ambiguity and stationarity.

ambiguity and the stationarity. The rank is determined according to **Table 1**. If the ambiguity is less than 0.5, the robots can recognize objects because of the reasons explained in Sections 2.2.2 and 2.3.2. Also if the stationarity is less than 0.5, we estimate that the feature has enough stationarity tentatively. Because the robots can easily recognize the object by using the feature that has the lowest rank, the feature is selected as the most adequate. And if various features have the lowest rank, the feature with low ambiguity is selected. **Fig. 17** is a graph of the ambiguity and the stationarity of **Fig. 15**, plotted on each axis. In **Fig. 17**, the better the feature is, the closer to the origin it appears.

4. Autonomous Landmark Generation

4.1. Definition of Landmark

In this section, we define the conditions under which objects can become landmarks. In order to determine a landmark, we introduce two evaluation factors; saliency and stationarity. Saliency means that an object has unique characteristics compared to other objects. For example, an object has a unique visual feature such as color, shape, or texture compared to other objects. Also some objects have unique physical or semantic relations between them, such as constellations. This means that we can evaluate saliency based on the ambiguity as defined in Section 2.4. Stationarity means that the time rate of change of the saliency is low or repeats the cycle. We already defined stationarity in Section 2.4. We deem that the object for which the ambiguity and the stationarity are determined can be used as landmark.

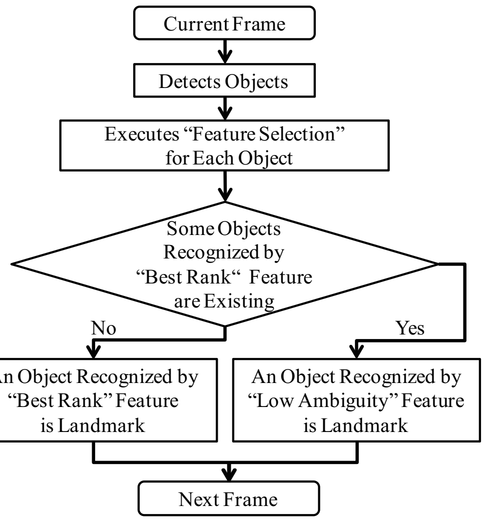

Fig. 18. Flowchart of autonomous landmark generation.

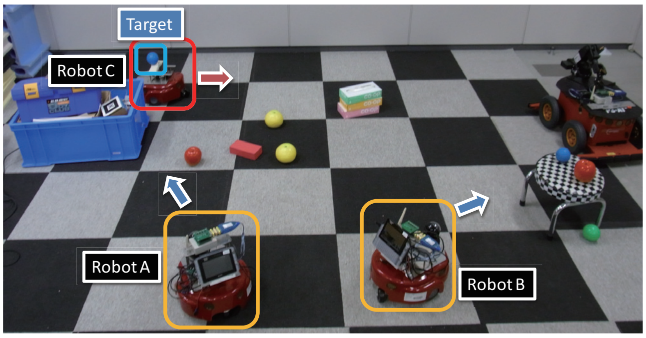

Fig. 19. Experimental environment.

4.2. Method to Generate Landmark

Figure 18 shows the flowchart of autonomous landmark generation. First, the robots execute "Feature Selection" on each object that they try to recognize, and then they select the best feature to use for the recognition. Next, the robots compare each feature rank. Finally, the robots determine which object recognized has the lowest feature rank, in other words the object that was recognized most accurately, and consider it a landmark. If several objects are found to have the lowest feature rank, the robots consider the object with the lowest ambiguity feature to be the landmark.

5. Experiment

5.1. Experimental Conditions

The aim of this experiment is to perform cognitive sharing of the blue ball based on the autonomous landmark-generation method. **Fig. 19** shows the experimental environment. We assign the feature (color and shape) of tracking the target beforehand only to Robot A. Any information is not provided preliminarily to Robot B, thus it searches the target by using the only information given by Robot A. Robot C only carries the blue ball that is the

Table 2. The cognitive ability of robots.

Color	Blue, Red, Green, Yellow
Shape	Circle or Other Shape

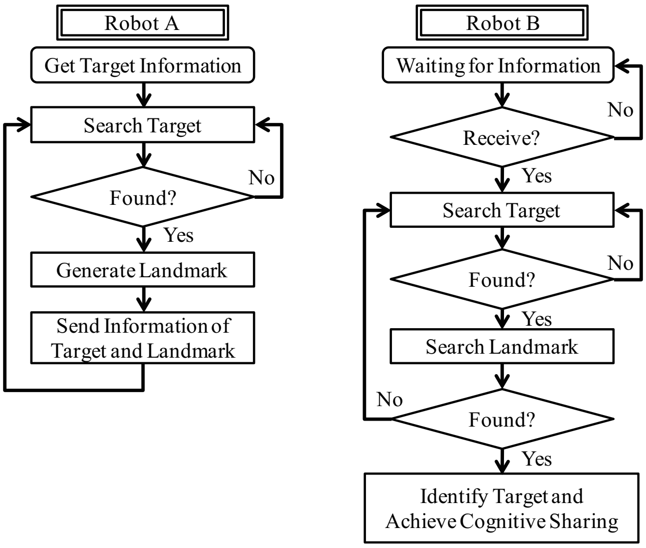

Fig. 20. Flowchart of cognitive sharing on robot communication.

tracking target and it never interlopes with Robot A or B by using communication, etc. Robot C is operated by a human. The blue arrows point in the initial direction of each Robot's camera. The red arrow points in the direction of motion of Robot C. Also, Robot A and B can recognize the object that has the features listed in **Table 2**.

5.2. Cognitive Sharing on Robot Communication

Figure 20 shows the flowchart of the cognitive-sharing process performed by the robots in this experiment. First we discuss Robot A. It searches the target until it can find the tracking-target information given previously. If it finds the target, it generates the landmark based on the aforementioned ambiguity and stationarity. If it generates the landmark, it sends the information of this landmark (color and shape) and of the target to Robot B. Otherwise, if it cannot generate the landmark, it informs Robot B accordingly. It performs this process at each frame. Next we discuss Robot B. Until it receives the information from Robot A, it is in standby condition. When it receives the information, first it searches around the target that has the desired features. If it finds the target, then it searches for the object that has the features included in the received information of the landmark. On the other hand, if it cannot find the landmark, it deems that the candidate for tracking object is not the object that Robot A is tracking, so it searches the tracking target again. If it finds both the received target and the object that has same features as the landmark, it can identify the candidate as the object that Robot A is tracking; thus we can estimate the success of the cognitive sharing.

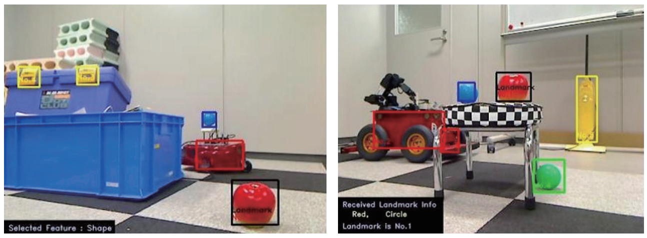

Fig. 21. Field of view of the robots in frame 34. The left image is of Robot A. The right image is of Robot B.

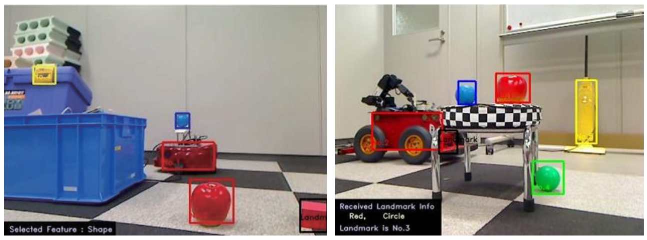

Fig. 22. Field of view of the robots in frame 72.

Fig. 23. Field of view of the robots in frame 112.

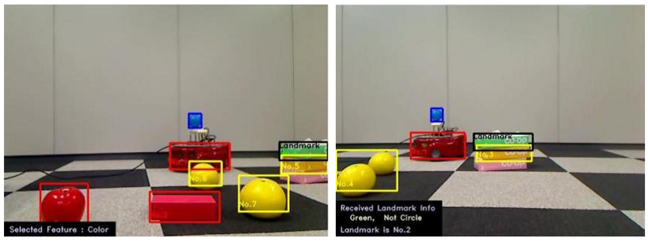

Fig. 24. Field of view of the robots in frame 154.

5.3. Experimental Results

We focus on and explain some important steps in the experiment. The fields of view of Robot A and Robot B are shown in **Figs. 21–24**. The left images correspond to Robot A and the right images to Robot B. **Figs. 25–28** show graphs of each object's ambiguity and stationarity that Robot A plots in real time. **Tables 3–6** are radical data that are plotted in **Figs. 25–28**. "No." is the number of each object shown in **Figs. 21–24** and "T" indicates the tracking target. "A" denotes Ambiguity, "S" is Stationarity, and "R" is Rank. **Figure 29** shows the transition of ambiguity of the tracking target which was observed by Robot A. First we consider the transition of ambiguity and feature selection with respect to the environment changes. In **Figs. 21** and **22**, the blue object has a higher proportion in the field of view of Robot A. In fact, in **Fig. 29**, the ambiguity of the color shows the highest value through

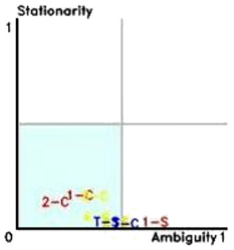

Fig. 25. Feature eval. in frame 34.

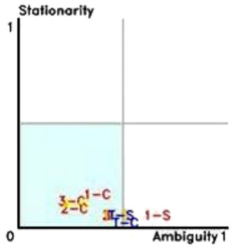

Fig. 26. Feature eval. in frame 72.

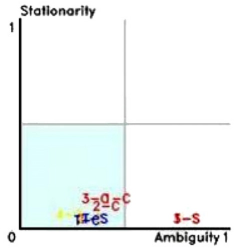

Fig. 27. Feature eval. in frame 112.

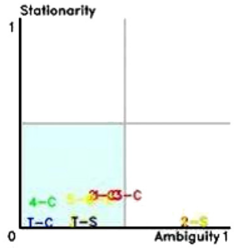

Fig. 28. Feature eval. in frame 154.

Table 3. Feature evaluation data in frame 34.

No.	Color	A	S	R	Shape	A	S	R
1	Red	0.234	0.138	1	Not Circle	0.595	0.011	2
2	Red	0.118	0.104	1	Circle	0.405	0.009	1
3	Yellow	0.308	0.134	1	Circle	0.405	0.009	1
4	Yellow	0.314	0.034	1	Circle	0.405	0.009	1
T	Blue	0.505	0.003	2	Circle	0.405	0.009	1

Table 4. Feature evaluation data in frame 72.

No.	Color	A	S	R	Shape	A	S	R
1	Red	0.309	0.138	1	Not Circle	0.596	0.038	2
2	Red	0.202	0.071	1	Circle	0.404	0.038	1
3	Red	0.190	0.104	1	Circle	0.404	0.038	1
4	Yellow	0.211	0.093	1	Circle	0.404	0.038	1
T	Blue	0.501	0.001	2	Circle	0.404	0.038	1

Table 5. Feature evaluation data in frame 112.

No.	Color	A	S	R	Shape	A	S	R
1	Red	0.396	0.121	1	Not Circle	0.730	0.024	2
2	Red	0.345	0.087	1	Circle	0.270	0.024	1
3	Red	0.292	0.121	1	Not Circle	0.730	0.024	2
4	Yellow	0.168	0.045	1	Circle	0.270	0.024	1
T	Blue	0.255	0.018	1	Circle	0.270	0.024	1

Table 6. Feature evaluation data in frame 154.

No.	Color	A	S	R	Shape	A	S	R
1	Red	0.346	0.135	1	Not Circle	0.764	0.007	2
2	Red	0.324	0.138	1	Not Circle	0.764	0.007	2
3	Red	0.452	0.132	1	Circle	0.236	0.007	1
4	Green	0.062	0.103	1	Not Circle	0.764	0.013	2
5	Yellow	0.220	0.115	1	Not Circle	0.764	0.011	2
6	Yellow	0.319	0.128	1	Circle	0.236	0.024	1
7	Yellow	0.243	0.015	1	Circle	0.236	0.024	1
T	Blue	0.038	0.002	1	Circle	0.236	0.024	1

all of the data. Reading out the data in column "T" of **Tables 3** and **4**, the color rank is 2 and the shape rank is 1. Consequently, Robot A is recognizing the tracking target based on the shape feature. Secondly, in **Figs. 23** and **24**, the proportion of the blue object in the field of view of Robot A is decreasing. Indeed, the color ambiguity shows a decreasing trend in **Fig. 29**. Reading out the data in column "T" of **Tables 5** and **6**, the color rank and the shape rank are both 1. So comparing each ambiguity we find that the color ambiguity has a lower value and therefore Robot A is recognizing the tracking target based on the color information. As described above, the surrounding environment changes with the movement of the tracking target and the robot, and the ambiguity reflects these

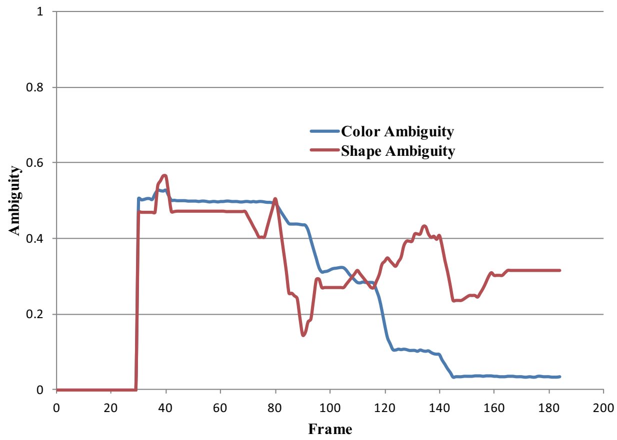

Fig. 29. Transition of ambiguities.

changes. Also, based on the ambiguity and the stationarity, the robot is recognizing the tracking target correctly. Now we discuss about the autonomous landmark generation. In **Fig. 21**, Robot A is recognizing object No.2 (red circle at the lower right) as the landmark. According to the method of landmark generation, comparing the rank of each object's color and shape feature, the rank values are equal to 1, except that of the shape feature of No.1. The comparison also shows that the ambiguity of the color feature of No.2 has the lowest value. So according to the process described in the preceding section, Robot A sends information (red and circular) about No.2 as the landmark to Robot B. On the other hand, in the field of view of Robot B in **Fig. 21**, there are objects that have the same features as the tracking target and as the landmark which are received from Robot A, and thus we know that it is recognizing them. It means that the cognitive sharing is successfully done, but practically each robot is viewing the different objects so that wrong cognitive sharing can be overcome. In **Fig. 22**, the landmark that Robot A generates becomes No.3 (red block at the lower right). Comparing the value in the same way as before in **Table 4**, we know that it becomes the landmark as the object of No.3 is recognized based on the color feature. Robot A sends the information of the new landmark to Robot B, but there are still objects like the tracking target and the landmark in the field of view of Robot B, so that wrong cognitive sharing is overcome. In **Fig. 23**, Robot A is recognizing No.4 (yellow circle (lemon) on the right) as the landmark. The red objects increased compared to **Figs. 21** and **22**, and we think that the color ambiguity of the red object that was the landmark until now is increasing. In fact, if we check **Table 4**, we can see that the ambiguity of the red objects (Nos.1–3) is increasing. In contrast, confirming the table according to the method of landmark generation, we know that the object becomes the landmark as the object of No.2 is recognized based on the color feature. Robot A sends the information (yellow and circular) of the newly received landmark to Robot B. Then Robot B first confirms that it was recognizing the wrong object as the tracking target because the object that has the same features as the landmark doesn't exist in the field of view of Robot B. After that, Robot B starts searching around. In **Fig. 24**, the landmark that Robot A generates becomes No.4 (green box on the right). Comparing the value according to the method of landmark generation in **Table 6**, we know that it becomes the landmark as the object of No.4 is recognized based on the color feature. Robot A sends the information (not circle, green) of the new landmark to Robot B. Then Robot B recognizes both new objects that have the same features as the tracking target and the landmark whose information was received from Robot A. This allows us to say that the cognitive sharing was successfully done. As seen above, we make sure that the cognitive sharing is attainable by generating the landmark around the tracking target and searching both the tracking target and the landmark. Finally we discuss the reason why stationarity values in **Tables 3–6** are globally low. This time, the robot that carries the tracking target moves slowly, so the movement of the robot's field of view is also slow. Consequently, we consider that stationarity has a low value because the changes in the environment which produce a change in ambiguity arise gradually, and therefore the change in ambiguity is also gradual.

6. Conclusion

In this paper we set as our goal the advancement of object recognition and the implementation of cognitive sharing among robots, which is a big problem at a multi-robot cooperative level. For the former, the solution is the selection of the best feature by the robot autonomously, whereas for the latter the solution is the generation of a landmark by the robot autonomously and subsequently the use of that generated landmark. Thus, we first proposed the use of ambiguity and stationarity, which are the indexes used to gauge the effectiveness with respect to the feature of color and shape. According to these indexes, we proposed a method for selecting the best feature and for generating the landmark autonomously. Based on our experiment on cooperative object tracking using a multi-robot system, we indicate that the robots select the best feature depending on the environment which varies from hour to hour based on the ambiguity and the stationarity. Also, we confirm that successful cognitive sharing among robots can be achieved by considering the object that is the most easily recognized on a case-by-case basis autonomously to be the landmark and sharing the relevant information.

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Name:
Takayuki Umeda

Affiliation:
Department of Micro System Engineering, Nagoya University

Address:
1 Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan

Brief Biographical History:
2012- Joined Nippon Telegraph and Telephone Corporation

Membership in Academic Societies:
• The Japan Society of Mechanical Engineers (JSME)

Name:
Kosuke Sekiyama

Affiliation:
Professor, Department of Micro System Engineering, Nagoya University

Address:
1 Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan

Brief Biographical History:
1997- Research Associate, Department of Micro-Nano System Engineering, Nagoya University
1998- Lecturer, The Science University of Tokyo, Suwa College
2001- Associate Professor, Department of Human and Artificial Intelligent System, Fukui University
2006- Associate Professor, Department of Micro-Nano System Engineering, Nagoya University

Main Works:
• "Self-referential Structure in Collective Agent System – Carrier Sequence Control of AGV Transportation System based on Diversity-regulation of Strategy –," Trans. of the Society of Instrument and Control Engineers, Vol.E-2, No.1, pp. 150-159, 2002.
• "A PSO-based Mobile Robot for Odor Source Localization in Extreme Dynamic Advection-Diffusion Environment with Obstacle: Theory, Simulation and Measurement," IEEE Computational Intelligence Magazine, Vol.2, Issue 2, pp. 37-51, May 2007.

Membership in Academic Societies:
• The Japan Society of Mechanical Engineer (JSME)
• The Robotic Society of Japan (RSJ)
• The Society of Instrument and Control Engineer (SICE)

Name:
Toshio Fukuda

Affiliation:
Professor, Department of Micro System Engineering, Nagoya University

Address:
1 Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan

Brief Biographical History:
1973 Received M.E. from The University of Tokyo
1977 Received Dr.Eng. from The University of Tokyo
1977- Joined the National Mechanical Engineering Laboratory
1979 Visiting Researcher Fellow, the University of Stuttgart
1982- Joined the Science University of Tokyo
1989- Joined Nagoya University

Main Works:
• "Micromechatronics, Handbook of Industrial Robotics," Second Ed., Chapter 10, Wily & Sons Inc., pp. 187-198, 1999.
• "Self-Scaling Reinforcement Learning for Fuzzy Logic Controller – Application to Motion Control for Two-Link Brachiation Robot," IEEE Trans. on Industrial Electronics, Vol.46, No.6, pp. 1123-1131, 1999.
• "Assembly of Nanodevices with Carbon Nanotubes through Nanorobotic Manipulation," Proc. of IEEE Vol.91, No.11, pp. 1803-1818, 2003.

Membership in Academic Societies:
• Institute of Electrical and Electronics Engineers (IEEE), Fellow, Region 10 Director
• International Fuzzy System Association (IFSA)
• The Society of Instrument and Control Engineers, Japan (SICE), Fellow
• The Japan Society of Mechanical Engineers (JSME), Fellow
• The Robotic Society of Japan (RSJ), Fellow, Board of Directors
• The Virtual Reality Society of Japan (VRSJ), Fellow