

Consensus Making Algorithms based on Invariants Perception for Cognitive Sharing in Multi-Robot

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Abstract—Visual recognition in multi-robot systems is afflicted with a peculiar problem that observations from different viewpoints present different perspectives. Moreover, a representation of the same target object is highly affected by the viewpoint or environmental condition. Hence, realizing cognitive sharing of the object among robots in an unconstructed environment has become challenging. To cope with this issue, we have proposed a Hierarchical Invariants Perception Model (HIPM) in which multiple representations; color, shape, geometric relation, are dynamically evaluated and selected by the robot. In this paper, we propose consensus-making algorithms to acquire viewpoint-invariant representations. Experimental results show the ability of cognitive sharing significantly improved by the proposed method.

Keywords—cognitive sharing; multi-robot; consensus making

I. INTRODUCTION

Cognitive sharing of an object is a primary issue in multi-robot task execution, where robots with different perspective are expected to cooperate in our daily unstructured environment. As robots engage in more varied and difficult tasks, they will become a ubiquitous part of our daily life in the future [1]. Researchers generally agree that multi-robot systems of inherently distributed character may behave more robustly and effectively and accomplish cooperative tasks that are not possible for single robot systems [2].

However, cognitive sharing methods in conventional works are generally difficult to be applied to unstructured environment. The conventional cognitive sharing has been based on the premise that the target is attached by an artificial marker such as RFID [3] and QR code [4], and that the target is a single-colored sphere [5].

We deem that visual information is suitable for the cognitive sharing in unstructured environment. One of the main issues in the cognitive sharing is to avoid misrecognition of the target object. Since visual information gives many kinds of representations of an object, we deem that, by using a combination of the representations, robots can verify whether or not they observe the same object. Although the cognitive sharing may be realized by sharing a global position of the target, localization errors by robots will make difficult cognitive sharing based on positional information. The position of the target in a global coordinate with errors only enables robots to share a region of interest (ROI).

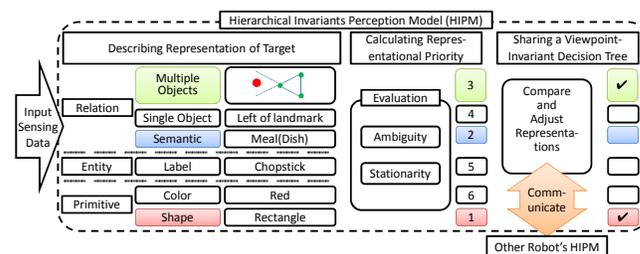


Figure 1. Hierarchical Invariants Perception Model

However, visual recognition in multi-robot systems has a peculiar problem that representations are highly affected by the robot's viewpoint and environmental condition. Since observations from different viewpoints present different representations, all representations cannot be shared. Also, unstructured environments abound with unavoidable disturbances, such as illumination changes, object occlusion and sensor faults, that would disturb cognitive sharing and even object recognition.

To cope with these issues, we have proposed a Hierarchical Invariants Perception Model (HIPM) [6] which deals with the cognitive sharing and object tracking simultaneously (Figure 1). A robot describes different classes of representation from sensing data (Describing Representations of Target), and evaluates the *ambiguity*, which estimates the risk of recognition failures for the target in the ROI, and *stationarity* which indicates the steadiness of the ambiguity over time. The robot selects a unique and stable representation based on ambiguity and stationarity (Calculating Representational Priority). Then the robot combines the representations and constructs a decision tree. By comparing and adjusting the representations in the decision tree through communication, robots reach a consensus (i.e., what representations can be shared). Finally, when the robots share the same decision tree, the target is identified (Sharing Viewpoint-Invariant Decision Tree).

In this paper, we extend the HIPM in that a definition of a relation representation and sharing a viewpoint-invariant decision tree are formulated, and experimentally illustrated. Although we have proposed the technique of autonomous landmark generation [7], in which some peripheral objects near the target are selected as landmarks in real time to relate the target to the surroundings, problems resulting from different viewpoints are not considered and a geometric relation among the target and multiple-landmark has not been used.

This paper is organized as follows. The System overview is described in Section II. Visual representations; *primitive representation* and geometric relation-based representation are presented in Section III. The method of identify the target and consensus-making algorithms are elaborated in Section IV. Experimental results are described in Section V. Finally, the conclusions are discussed in Section VI.

II. SYSTEM OVERVIEW

The purpose of the proposed approach is to share one target object in unstructured environment between two robots: robot A, which recognizes the target, and robot B, which does not know any information on the target. Several assumptions are made as follows.

(a) Environment: Some objects in the environment are similar to the target. The objects do not move. An appearance of the objects may change as a result of a change in viewpoint. An occlusion of the objects may occur.

(b) Robots: The robots can localize themselves though the localization has errors and are equipped with a RGBD sensor.

The proposed approach based on the HIPM has the two features:

- **Describing representations of the target** (in Section III) Robot A describes representations of the target from a RGBD image. In this paper, color, shape and geometric relation-based representation (GRR) are employed.
- **Sharing viewpoint-invariant decision tree** (in Section IV) Robot A constructs a decision tree, which is a suitable combination of the representations for identifying the target from the viewpoint of robot A. Robot B receives the decision tree and decides which representations are viewpoint-invariant. If robot B concludes the received decision tree includes non viewpoint-invariant representations, robot A sends a new decision tree. Through this process, robots share a viewpoint-invariant decision tree gradually.

Calculating representational priority is addressed in [7]. Since we do not assume drastic illumination changes, this component is not discussed in this paper.

III. DESCRIBING REPRESENTATIONS OF TARGET

A. Primitive Representation

We employ color and shape features as the basic representations to recognize an object, which are referred to as *primitive representation* in this paper. In visual recognition, image features (e.g., color [8], shape [9], and feature point [10]) have been used to recognize an object. Although feature points may be salient and therefore suitable for object recognition, they are susceptible to viewpoint changes. However, color and shape features tend to be robust against viewpoint changes.

Because the robots have different viewpoint, the primitive representation should be invariant with respect to scale and illumination changes in the visual recognition. A hue histogram is known to be an invariant representation with respect to scale, illumination direction, and angle changes [11]. In this paper,

the histogram similarity function is expressed by histogram intersection [12]. Histogram intersection is computationally efficient and robust against partial occlusion and resolution changes. The histogram axis is divided into 32 sections for computational efficiency and recognition accuracy. The similarity of color representation S_c is calculated from

$$S_c(H^a, H^b) = \sum_{i=1}^{32} \min(H^a(i), H^b(i)), \quad (1)$$

where H^a and H^b represent the hue histogram of object O_a and O_b respectively, and $H(i)$ represents the value of i -th histogram's bin.

Also, hu moments of a contour is used as a shape representation in this paper. Hu moments are invariant with respect to scale changes and rotation. By following the definition in [14], the similarity between two moments can be calculated

$$S_s(h^a, h^b) = \sum_{i=1}^7 \left| \frac{m^a(i) - m^b(i)}{m^a(i)} \right|, \quad (2)$$

where,

$$m(i) = \text{sign}(h(i)) \cdot \log|h(i)|,$$

h^a and h^b represent hu moments of object O_a and O_b respectively, and $h(i)$ represents the value of i -th hu momemts.

B. Object Segmentation

To describe the primitive representation of each object, the input image has to be divided into objects and the other areas, and the boundaries have to be contours of objects. In general, a computationally efficient segmentation method is required because the robots are supposed to move around. In this paper, we employ a segmentation method based on the depth information obtained using an RGBD sensor [15]. RGBD sensors (Kinect or Xtion) can output sensing data at a frame rate of 30 Hz and this method can extract accurate contours by using the depth information. Fortunately, because the depth information can be captured under any ambient light conditions, the shape representation is invariant against arbitrary illumination changes.

C. Similar Primitive Representation from Different Viewpoints

In general, a primitive representation will be highly affected by changes in viewpoint. However, empirically, a similarity of primitive representation between the same object from different viewpoints lies within a certain range.

Assume a color representation H^a and shape representation h^a of an object O_a are sent from robot A. When a color representation H^b of object O_b , which is perceived by robot B, satisfies

$$S_c(H^a, H^b) \geq 0.7, \quad (3)$$

we define O_b has a similar color representation to H^a . Also, when a shape representation h^b of O_b satisfies

$$S_s(h^a, h^b) \leq 0.3. \quad (4)$$

we define O_b has a similar shape representation to h^a .

If robot B perceives only one similar color (shape) representation to H^a (h^a) after sharing a ROI, define H^a (h^a) as viewpoint-invariant representation. If H^a or h^a is viewpoint-invariant, O_a and O_b may be the same object.

D. Geometric Relation-Based Representation

In this paper, as the relation representation, we use geometric relation between the target and sharable surroundings. Use of geometric relation offers two advantages: 1. the error for the relative positions of objects is comparably smaller than the error of global position and 2. the information is independent of robot localization and odometry. Therefore, this relation is viewpoint-invariant.

Two processes are needed to form a GRR as follows.

- 1) Select candidate objects of GRR components that have a salient primitive representation.
- 2) Describe the geometric relation among the target and the components of GRR based on a distance information.

An object which has no similar representation from robot A's viewpoint is likely to be identified uniquely. Therefore, such objects are suitable for candidates of GRR components.

Three objects of the same kind of primitive representation (e.g., three objects which have unique color representations) are selected from the candidates, and a triangle is formed. The reason why the same kind of primitive representation should be selected is that color and shape representations are invariant with respect to different disturbances (e.g., color representation is invariant to partial occlusion and shape representation is invariant to changes in lightning conditions). The reason why a triangle is chosen is that it is the minimum unit needed to divide a flat space into a closed area and other geometric shapes can be represented by a combination of triangles.

A GRR divides the recognition area into 7 areas A_a ($a \in \{1, 2, \dots, 7\}$). The decomposed area A_a is represented by the triple set of + and - sign as shown in Figure 2. The decomposed area where the target belongs is denoted by A_t . Assuming l candidates for the GRR components, the number of constructed GRR m is ${}^l C_3$. A GRR is regarded as viewpoint-invariant when all GRR components are viewpoint-invariant.

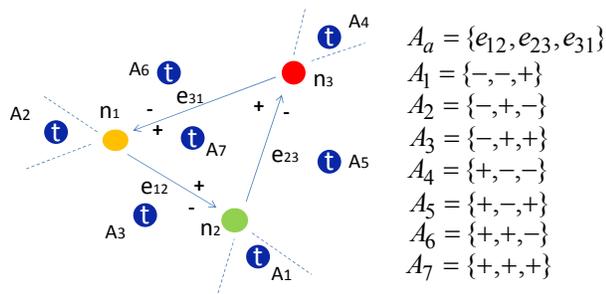


Figure 2. Representation of Target Position. The components of a GRR are denoted by n_1, n_2, n_3 and connected in the counterclockwise direction. A link vector (e_{12}, e_{23}, e_{31}) which connects to the components will decompose the recognition area into two domains. The left-side of the link vector where each vector is linked counterclockwise is denoted as the positive sign (+) and the right-side of each vector is denoted as the negative sign (-).

IV. SHARING VIEWPOINT-INVARIANT DECISION TREE

A. Construction of the Decision Tree

We use a binary decision tree that consists of combined representations to identify the target because it is very rare when the target object can be uniquely identified by means of a single representation. Such a limited case is the following:

- (i) When a primitive representation is employed, no similar representation is found closely to the target object.
- (ii) When a GRR is employed, only the target object is included in the decomposed area A_t of the GRR.

In order to construct the decision tree, we employ the branch and bound algorithm. In the cognitive sharing, since the data of the target class is only one, conventional methods (e.g., C4.5 and CART) cannot be used because these methods require adequate data to select an effective node.

The branch and bound algorithm has the advantage of constructing a decision tree that can minimize the required number of nodes. Redundant information may increase searching time because not all representations can be shared owing to appearance changes and occlusion. The solution to the problem resulting from viewpoint changes is discussed in Sec. IV-B.

The branch and bound algorithm is given as follows: Assume a set of n objects $O = \{O_1, O_2, \dots, O_n\}$, which is perceived by robot A. An object $O_i (\in O)$ is described by color representation i.e., hue histogram H^i , shape representation i.e., hu moments h^i and m GRRs $g_j^i (j \in M = \{1, 2, \dots, m\})$. From robot A's viewpoint, candidates of the target object $O_t (\in O)$ can be reduced by using the target's representations H^t, h^t, g_j^t according to

$$R_j = \{O_i \in O | O_i \in A_t^j\} \quad (j \in M), \quad (5)$$

$$R_{m+1} = \{O_i \in O | S_c(H^t, H^i) \geq 0.7\}, \quad (6)$$

$$R_{m+2} = \{O_i \in O | S_s(h^t, h^i) \leq 0.3\}. \quad (7)$$

Here R_j, R_{m+1} , and R_{m+2} represent a set of candidates reduced by using similarity criteria g_j^t, h^t , and H^t respectively.

(i) Objective Function and Constraint Condition

Let us denote a collection of the target's candidate sets by $R = \{R_1, R_2, \dots, R_m, R_{m+1}, R_{m+2}\}$. The goal is to find a combination of the target's representations that can narrow candidate objects of the target down to one such that the number of tree nodes is minimized. The objective function and constraint condition are defined as follows:

$$\text{minimize } |X| = |\cap_{R_k \in R'} R_k|, \quad (R' \subset R), \quad (8)$$

$$\text{subject to } |X| \geq 1, \quad |R'| \leq 3, \quad (9)$$

where $|\cdot|$ represents the cardinality of a set. If $R' = \{R_1, R_{m+1}\}$, 1st GRR g_1^t and color representation H^t are employed as nodes of a decision tree. In order to reduce redundant information, the number of nodes $|R'|$ is limited to 3.

(ii) Branching

Subproblem P_i (breadth first search)

Minimize $|X|$ subject to $|R'| = i \quad (i \in \{1, 2, 3\})$

- (iii) **Bounding**
 Prune if $|X| \leq z$. z is the minimum upper bound seen among subproblems examined so far.
 Finish if $|X| = 1$.

B. Comparing and Adjusting Representations

As mentioned in Sec. IV-A, a decision tree sent by robot A can include representations which cannot be shared between the robots resulting from different viewpoints. In this section, we discuss how two robots perceive viewpoint-invariant representations and share a viewpoint-invariant decision tree through communication. Figure 3 shows a state transition diagram of robot A and robot B. The consensus-making algorithms are composed of four functional parts; ROI sharing, searching, invariants perception, and decision tree adjustment. We explain how robot B changes its state mainly because robot A changes its state according to robot B's request.

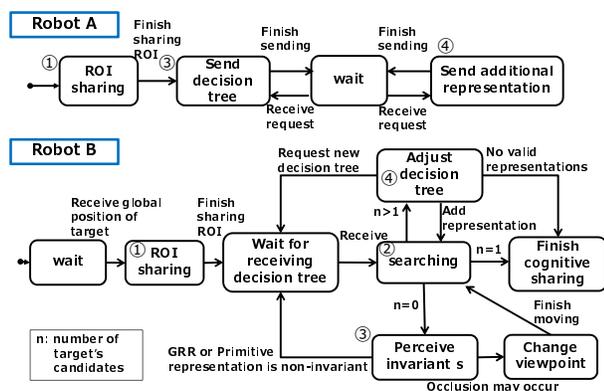


Figure 3. State Transition Diagram of Robot A and B

1) *Sharing ROI* (Figure 3-①): To verify whether or not a representation is viewpoint-invariant, a ROI has to be shared. Without sharing the ROI, robots cannot determine the cause of the misrecognition by searching another region or a non-viewpoint-invariant representation.

In this paper, since we assume robots can localize themselves and get depth information from RGBD sensor, robots can calculate a global position of objects. We define a region around a global position of the target as a ROI. The robots share the ROI by sharing the global position of the target. However, since the robot localization has errors, cognitive sharing cannot be achieved by only using the positional information.

Robot A sends the global position of the target to robot B. On receiving, robot B moves to a position only a certain distance away from the global position of the target and finish sharing the ROI. In this paper, we define the distance as 1.5m.

2) *Searching* (Figure 3-②): After sharing ROI, robot A sends a decision tree. On receiving the decision tree, robot B starts searching. Since robot B can calculate a position of objects in robo-centric coordinate, robot B searches while making a map of objects. Considering an area that has been searched, robot B decides where to search. After rotation, robot B perceives objects and updates the map. Robot B compares objects in the map with the received decision tree and moves to a position where objects which has identified representations in the decision tree can be observed.

When all representations in the decision tree are identified and candidates of the target object are found, robot B change the state: change the state to finish cognitive sharing if the number of the candidates is one, change the state to adjust a decision tree if the number of the candidates is more than one. When the number of the candidates is zero or all representations in the decision tree is not identified, robot B lasts searching. Robot B change the state to invariants perception when finishes searching around the ROI.

3) *Invariants Perception* (Figure 3-③): Representations which are not identified though robot B finishes searching around the ROI are regarded as non viewpoint-invariant representations. Robot B takes different actions according to a kind of the non-viewpoint-invariant representation.

- (i) **Primitive representation of the target**

Two situations are conceivable: the appearance of the target may change or the occlusion of the target occurs. In order to verify whether the occlusion occurs or not, robot B changes its viewpoint and searches around the ROI again. In this paper, changing viewpoint is achieved by moving a certain distance to a tangential direction of a circle whose center is the received global position of the target and the distance is defined as 0.8[m] empirically. If the primitive representation cannot be identified even after changing viewpoint, robot B requires robot A to send a new decision tree which does not include the primitive representation because its description is likely to be varied.

- (ii) **GRR**

When not all components of a GRR in the received decision tree are identified, robot B requires robot A to send a new decision tree which does not include the unidentifiable components of the GRR. When the GRR is shared but the number of candidates narrowed down by using the GRR is zero, robot B changes its viewpoint and begins searching again because an occlusion of the target objects may occurs. If the candidates are not found after changing viewpoint, the GRR is regarded as non-viewpoint invariant. Then, robot B requires robot A to send a new decision tree.

4) *Decision Tree Adjustment*(Figure 3-④): Even though the robots successfully share viewpoint-invariant representations, robot B sometimes may fail to identify the target when the primitive representation is not viewpoint-invariant. For example, this would occur when an object out of robot A's view exists in A_t of the GRR or when the objects near the target in A_t change their appearance.

In these situations, robot B has to determine what information is needed autonomously. Robot B calculates the similarity of primitive representations among the candidates as reduced by using the received decision tree. If the primitive representations of the candidates are not similar, robot B requests the primitive representation. Then, robot B adds the primitive representation to the decision tree and tries to identify the target. Robot B also requests another decision tree if the number of candidates cannot be reduced by using only the primitive representation. Robot B will finish searching when

the number of candidates is reduced to one or when the number of candidates obtained by using the decision tree is the same between the robots.

V. EXPERIMENT

A. Experimental Conditions

This experiment demonstrates that the proposed approach has robustness against following problems:

- Robot B mistakes the target for a similar object.
- Not all representations can be shared because an occlusion and appearance change may occur resulting from different viewpoints.

The experiment environment is shown in Figure 4. Each robot (robot A: amigobot; robot B: Pioneer 3-AT) is equipped with a Xtion Pro Live and a communication module (OKI UDv4). The initial position and pose of a robot (x, y, θ) are defined by adding random noise w_1, w_2, w_3 with a Gaussian distribution having standard deviation 0.3 to true value $(x_{true}, y_{true}, \theta_{true})$.

$$(x, y, \theta) = (x_{true} + w_1, y_{true} + w_2, \theta_{true} + w_3). \quad (10)$$

The robots localize themselves using odometry. Robot A recognizes the target in the middle left of Figure 4 and robot B does not know *a priori* target information. There exists a similar object to the target in the environment in the middle of Figure 4 labeled as "dummy". We assume that dramatic illumination changes and the movement of objects will not occur during cooperation.

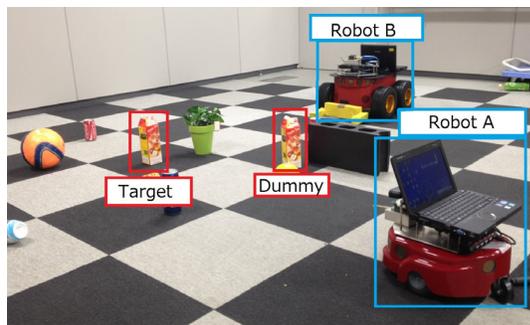


Figure 4. Experiment Environment

B. Experimental Result

Snapshots of the experiment are shown in Figure 5-9. The constructed decision tree is shown in the upper left of each image. Robot's action and communication condition are shown in the above each image. The red bounding box in the image represents the target and the blue bounding boxes represent identified components of the GRR. The objects with white crosses represent non viewpoint-invariant representations.

1) *ROI Sharing*: By $t = 3[s]$, robot B received the global position of the target and start sharing the ROI. By $t = 8[s]$, Robot B moved 1.5m away from the received global coordinate and finished ROI sharing (Figure 5).

Since the initial position of robots are added random noise, a target position estimated by robot B has an error as shown in Figure 10. Only using positional information of the target, robot B may fail to identify the target because the estimated

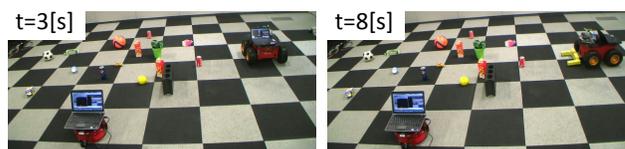


Figure 5. Snapshots of ROI sharing

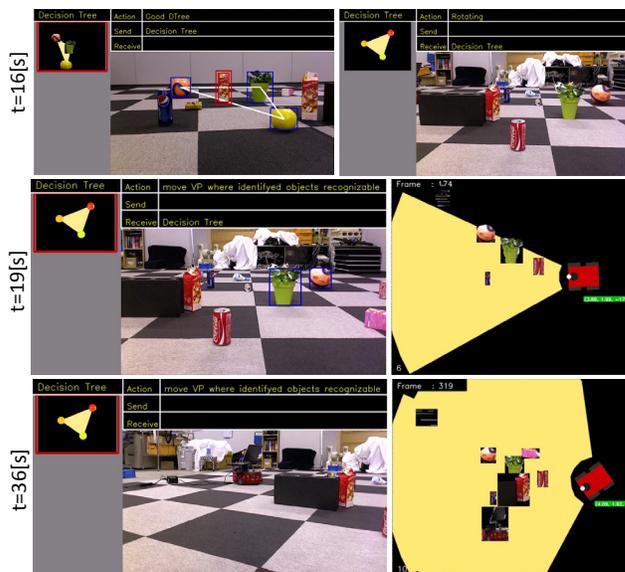


Figure 6. Snapshots of Searching (Top row: robot A's view (left), robot B's view (right). Middle and bottom row: robot B's view (left), a map made by robot B (right).)

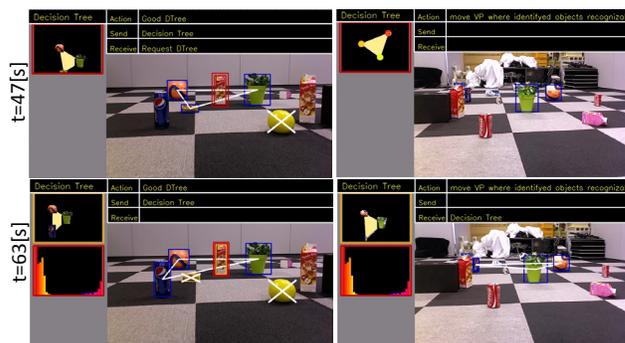


Figure 7. Snapshots of Invariants Perception (Left column: robot A's view. Right column: robot B's view.)

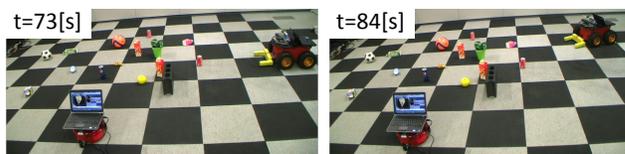


Figure 8. Snapshots of Change Viewpoint



Figure 9. Snapshots of Finish Cognitive Sharing. (Left: Robot B's view, Right: a map made by robot B)

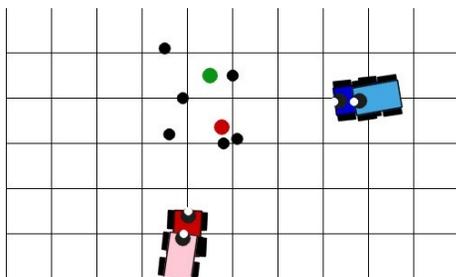


Figure 10. true and estimated position of robots and the target. Red robot: true position of robot A. Pink robot: robot A's position estimated by robot A. Blue robot: true position of robot B. Light Blue robot: robot B's position estimated by robot B. Green circle: true position of the target. Red circle: target position estimated by robot B. Black circles: surroundings near the target (not all). Lines are drawn at intervals of 0.5m.

position is closer to position of surroundings than the true position.

2) *Searching*: By $t = 16[s]$, robot B received the decision tree from robot A and started searching. By $t = 19[s]$, robot B found two components of the GRR and then continue searching in the ROI to find the rest of components. By $t = 36[s]$, although robot B finished searching in the ROI, robot B did not find the rest of the components. Therefore, robot B changed its state to Invariants Perception. (Figure 6)

3) *Invariants Perception*: By $t = 40[s]$, robot B regarded the unidentifiable component of the GRR as non-viewpoint-invariant, and required robot A to send a new decision tree which did not include the unidentified component of the GRR. In fact, an occlusion of the component occurred.

By $t = 47[s]$ (Figure 7), robot B received a new decision tree. However, one component of the GRR did not found. Therefore, robot B regarded it as non viewpoint invariant and required the new decision tree. In fact, the appearance of the component changed resulting from different viewpoints.

By $t = 43[s]$ (Figure 7), robot B received the new decision tree and succeeded in identifying the GRR in the decision tree. However, candidates of the target were not found in the decomposed area of the GRR. Robot B considered that the target was occluded, and changed its viewpoint.

By $t = 84[s]$, robot B finished changing its viewpoint by moving 0.8[m] to a tangential direction of a circle whose center is the received global position of the target as shown in Figure 8.

4) *Finish Cognitive Sharing*: By $t = 91[s]$ (Figure 9), robot B found a candidate of the target in the decomposed area in the new viewpoint. Because the color representation of the candidate corresponded with the color representation of the second tree node, robot B succeeded in sharing the target.

5) *Decision Tree adjustment*: Another experiment was conducted to demonstrate the necessity of decision tree adjustment as shown in Figure 11. By $t = 95[s]$, the robots shared the decision tree composed of the viewpoint-invariant representations. However, similar color object appeared in the decomposed area owing to an appearance change, so robot B did not make a difference between these candidates. Robot B determined the necessary representation autonomously and requested the

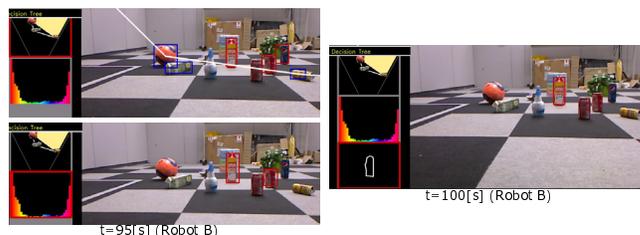


Figure 11. Snapshots of Other Experiment

shape representation in this situation. By $t = 100[s]$, robot B succeeded in cognitive sharing by adding the shape representation to the decision tree.

VI. CONCLUSION AND FUTURE WORK

We proposed cognitive sharing algorithm based on visual information. A decision tree including geometric relation-based representation allows robots to share precise ROI and avoid mistaking the target for a similar object. The Consensus-making algorithms serve to acquire viewpoint-invariant representations.

For future work, an important issue will be adaptation to disturbances. Although we assumed that dramatic illumination changes and the movement of objects would not occur in the experiment, such disturbances occur in unstructured environment. Evaluating ambiguity and stationarity in a HIPM, robots should select robust representations against a certain disturbance.

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