Robust and Accurate Detection of Object Orientation and ID Without Color Segmentation

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Abstract. This paper describes a novel approach to detecting orientation and identity of robots without color segmentation. The continuous DP matching calculates the similarity between the reference pattern and the input pattern by matching the intensity changes of the robot markers. After the continuous DP matching, a similarity value is used for object identification. Correspondences of the optimal route obtained by back tracing are used for estimating the robot's orientation. This method archives orientation estimations of less than 1 degree and robustness with respect to varying light conditions.

1 Introduction

To give optimal visual-feedback, in order to control a robot, it is important to raise the robustness and accuracy of the vision system. Especially, in the RoboCup Small Sized League(F180), a global vision system that is robust to unknown and varying lighting condition, is needed. The vision system which has been generally used, processes an image to identify and locate robots and the ball. For low-level vision, the color segmentation library, called CMVision [1], has been used to perform color segmentation and to connect components analysis to return colored regions in real time without special hardware. After the color segmentation, the process of object identification is employed based on the results of the color segmentation which is then followed by the process of the pose estimation of the robot. To raise the robustness with respect to varying light condition, color calibration [2] need to be done in advance, but requires minimal set up time.

In this paper, we propose a robust and accurate pattern matching method for identifying robots and estimating their orientations simultaneously without color segmentation. Our approach uses continuous DP matching to search for similar pattern, which is obtained by scanning at a constant radius from the center of the robot. The DP similarity value is used for object identification, and for obtaining the optimal route by back tracing to estimate its orientation. We realized robustness of object identification with respect to varying light conditions by taking advantage of the changes in intensity only.

In the following, the related work and our approach are described in section 2. Section 3 describes the method for robust and accurate object identification.

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The experimental results are shown in section 4. Section 5 discusses some of the advantages of the proposed method. Lastly, section 6 concludes the paper.

2 Related Work

In the Small Size League, one team must have a 50 mm blue colored circle centered on the top of its robot while the other team must have a 50 mm yellow patch. To detect the robot's orientation and to identify it, teams are allowed to add extra patches using up to three colors. Figure 1 shows examples of patterns found on the top of the robot.

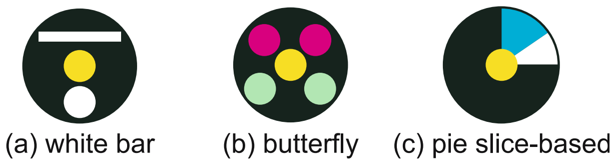


Fig. 1. Example of general identification patterns

Type (a), called "white bar", is used to calculate the pose of robot precisely. The robot's orientation is calculated using a white stripe and the least-squares method [3] or second-moment [4]. For identification, other sub patches are used.

Type (b), called "butterfly", has been reported in [5]. Geometric asymmetry can be used to find the rotational correspondence for orientation estimation.

Type (c), called "pie slice-based", is unique and is described in [6]. This method scans the circular pattern from markers on the robot. The angle resolution is not sufficient (8 degree) due to low resolution.

These methods use information from color segmentation to determine a robot's identity. Such colors have problems with brightness changes and non-uniform color intensity over the field, including sharp shadows.

2.1 Proposed Patch Pattern

Our approach uses only the changes in intensity obtained by scanning at a constant radius from the center of the robot and not by using the results of color segmentation. Therefore, we can paste suitably-colored patches on the top of the robot as shown in Figure 2. This makes a large number of different patterns for identification, and it's easy to modify patch patterns. Moreover, preparing the rule-based reference table by user for object identification is no longer necessary.

3 Object Identification

The DP matching calculates the similarity between reference pattern and input pattern by matching the intensity changes of the robot markers. After the DP

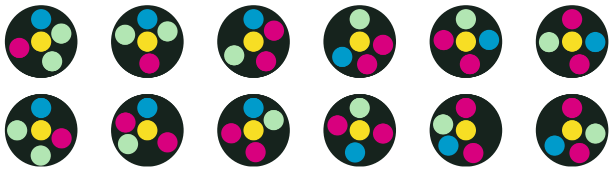


Fig. 2. Example of our ID plate

matching, a similarity value is used for identification. Correspondence of optimal route obtained by back tracing is used for estimating its orientation. The flow of the proposed method is as follows and shown in Figure 3:

1. Color conversion(RGB to YUV)
2. Detection of the center of blue/yellow colored circles
3. Converting to 1-dimensional signal by scanning at some constant radius from the center of the robot
4. Identifying our robots by continuous DP matching
5. Finding the robot's orientation by back tracing.

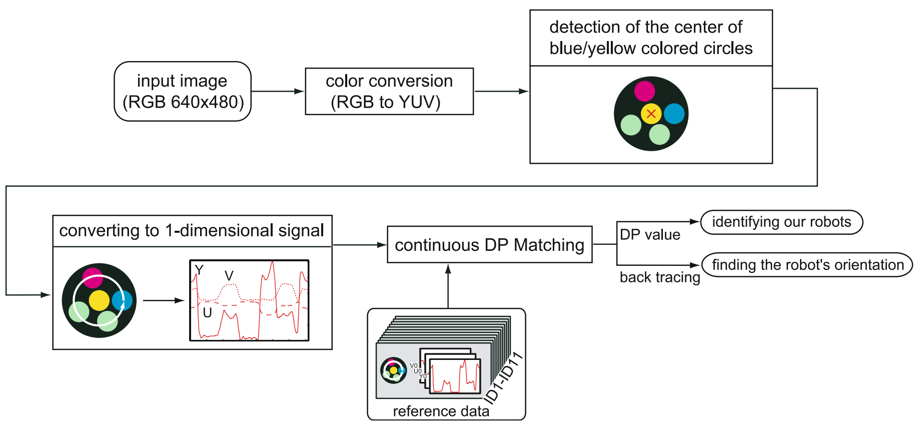


Fig. 3. Overview of our vision system

3.1 Detection of the Center of Blue/Yellow Colored Circle

It is important to detect the center of the blue/yellow colored circle because our approach uses this center position to convert to 1-dimensional signals for the object identification. The followings describe an algorithm for determining the center position of a circle given three points on a plane.

The three points determine a unique circle if, and only if, they are not on the same line. The relationship of these three points is expressed as:

$$(x_c - x_i)^2 + (y_c - y_i)^2 = (x_c - x_j)^2 + (y_c - y_j)^2 = (x_c - x_k)^2 + (y_c - y_k)^2. \quad (1)$$

where (x_c, y_c) is a center coordinate, three points on image are (x_i, y_i) (x_j, y_j) (x_k, y_k). Equation (1) is a linear simultaneous equation. Thus, (x_c, y_c) is determined by Gaussian elimination using the following steps:

Step1. Detect blue/yellow colored circle.
Step2. Extract contour points of the circle.
Step3. Select three points from contour points randomly, calculate center position (x_c, y_c) by equation (1).
Step4. Increment a count in the accumulator at point (x_c, y_c).
Step5. Step 3 and 4 are repeated 100 times.

Finally, the maximum number of votes is determined as the center of the main marker.

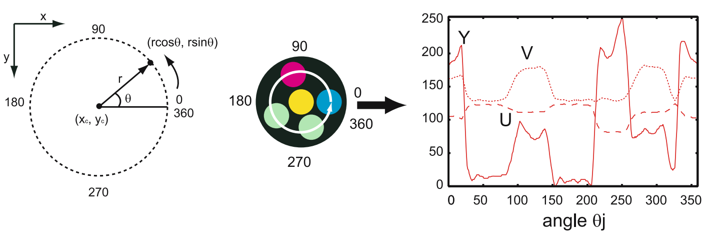
3.2 Converting to 1-Dimensional Signal

The intensity values of YUV on the top of the robot are obtained by scanning at a constant radius (r=10 pixel) from the detected center of the circle as shown in Figure 4. It is impossible to obtain the 359 points (1 degree each) on the circle's perimeter because of the low resolution image. To solve this problem, we apply the bilinear interpolation to estimate the robot's orientation with sub-pixel accuracy.

Image coordinate (x, y) for an angle θ is obtained by

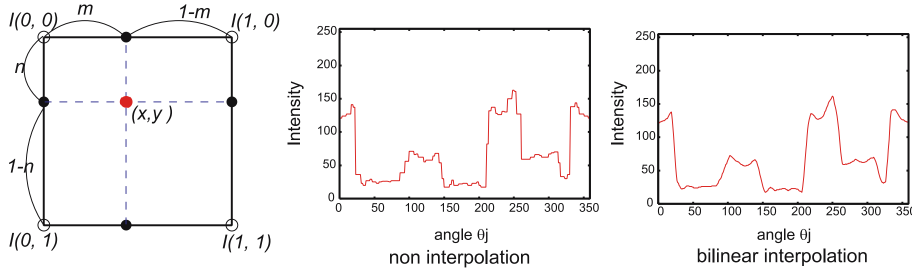
$$x = r\cos\theta + x_c, \qquad y = r\sin\theta + y_c \quad (2)$$

where (x_c, y_c) is the center position on the image coordinate. Since the values of (x, y) are real numbers, the intensity value $I(x, y)$ is interpolated by the bilinear interpolation method used for 2-dimensional operations, for instance



(a) scanning at a constant radius (b) converting to 1-dimensional signal

Fig. 4. Converting to 1-dimensional signal



(a) bilinear interpolation (b) example of interpolation

Fig. 5. Bilinear interpolation

magnifying an image. The interpolated value in intensity is calculated as shown in Figure 5(a)

$$
\begin{aligned}
I(x, y) = &(1-n)((1-m)I(0,0) + mI(1,0)) \\
&+ n((1-m)I(0,1) + mI(1,1))
\end{aligned}
\tag{3}
$$

Figure 5(b) shows the interpolated intensity values of Y. This can be useful to estimate the orientation angle with sub-pixel accuracy. Finally, the intensity values of Y normalized to 0∼255, U and V are obtained as a 1-dimensional signal from the circle patches on the robot as shown in Figure 4(b), and these values are expressed as:

$$
I(\theta_j) = I(r\cos\theta_j, r\sin\theta_j) \quad j = 0, \cdots, 359. \tag{4}
$$

3.3 Identifying Our Robots by the Continuous DP Matching

To uniquely distinguish a robot, the intensity values $I(\theta_j)$ as a reference pattern for each robots are registered initially by clicking with the mouse of points in the direction of the robot's front help to assign an ID to each robot. The continuous DP matching is performed to calculate a similarity between the reference patterns and the input pattern of the current image.

Continuous DP matching. The DP matching has been used in various area such as speech-recognition [7]. DP matching is a pattern matching algorithm with a nonlinear time-normalization effect. Timing differences between two signal patterns are eliminated by warping the axis of one, so that the maximum coincidence is attached as the minimized residual distance between them. A starting point of input pattern provided by scanning described in section 3.2 is not at the same position as the reference pattern. Therefore, continuous DP matching can be useful in computing the similarity distance by considering the lag of each starting point. The input pattern is repeated twice as $(1 < i < 2I)$ and this handling is shown in Figure 6.

In this implementation, the symmetrical DP path, shown in Figure 7(a), is used. Minimum accumulated distance is calculated by the following equations.

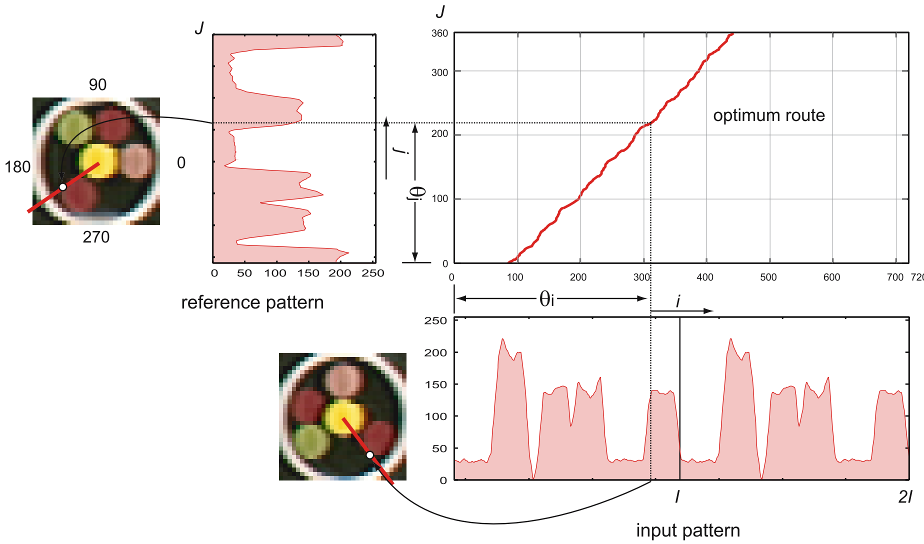


Fig. 6. Example of back tracing

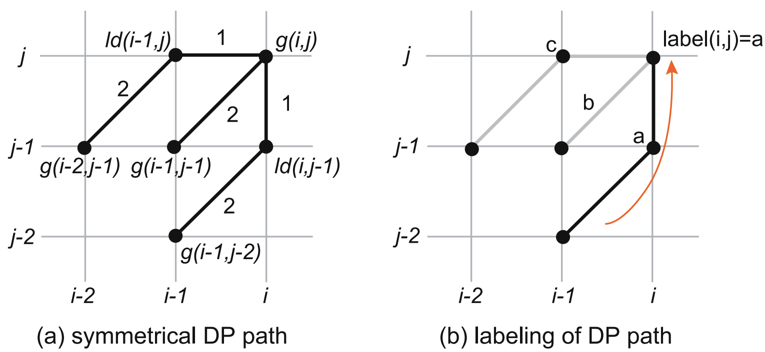


Fig. 7. Symmetrical DP path

Let the vertical axis represents reference pattern frame j, and the horizontal axis as input pattern frame i. Initial conditions are given as:

$$\begin{cases} g(i,0) = 0 & (i = 0, 1, \ldots, I) \\ g(0,j) = \infty & (j = 1, 2 \ldots, J) \end{cases} \tag{5}$$

where I and J are length of each patterns. The minimum accumulated distance $g(i,j)$ on the i frame and j frame are calculated by:

$$g(i,j) = \min \left\{ \begin{array}{ll} g(i-1, j-2) + 2 \cdot ld(i, j-1) & : (a) \\ g(i-1, j-1) + ld(i,j) & : (b) \\ g(i-2, j-1) + 2 \cdot ld(i-1, j) & : (c) \end{array} \right\} + ld(i,j). \tag{6}$$

Local distance $ld(i,j)$ on the point of (i,j) is computed as:

$$ld(i,j) = (I_t(\theta_i) - I_{t-1}(\theta_j))^2. \tag{7}$$

The length for the optimal route:

$$c(i,j) = \begin{cases} c(i-1,j-2)+3 & \!\!\!\!\big| if(a) \\ c(i-1,j-1)+2 & \!\!\!\!\big| if(b) \\ c(i-2,j-1)+3 & \!\!\!\!\big| if(c) \end{cases} \tag{8}$$

is used to obtain the normalized accumulated distance by:

$$G(i) = \frac{g(i,J)}{c(i,J)}. \tag{9}$$

Object ID recognition. The continuous DP matching is performed to calculate similarity distances for each reference pattern, when a blue/yellow circle of the robot is detected. The identity of the robot is determined by selecting the reference pattern which is given the minimum value of G.

3.4 Object Orientation Estimation by Back Tracing

To detect the robot's orientation, back tracing, which computes local corresponding points of input and reference patterns by referring the selected DP path, is performed as follows:

1. DP matching and labeling of the selected DP path
   While computing the minimum accumulated distance, the path selected by equation (6) is memorized with label a/b/c as shown in Figure 7(b).
2. Back tracing
   After normalizing minimum accumulated distance, the minimum value of $G(i,J)$ is selected as a starting point for the back tracing.

   $$i' = argmin_{(J/2 \le i \le 2I)} G(i,J) \tag{10}$$

   The optimum route is tracked by referring to the label, either 'a', 'b', or 'c' at each node. The DP path labeled 'a' means insert, and 'c' means delete. The path 'b' means that frame i and j are a pair of corresponding point. When path 'b' appears on the optimum route, the orientation of the current robot θ is estimated by:

   $$\theta = \theta_i - \theta_j \tag{11}$$

   where θ_i is the orientation angle of input pattern, and θ_j is reference pattern. This process is finished when the route, by back tracing, reaches the end point($j = 0$), and then the average of the angle θ points at the robot's orientation(front direction).

As we mentioned above, object orientation and ID are determined by the continuous DP matching and not color segmentation.

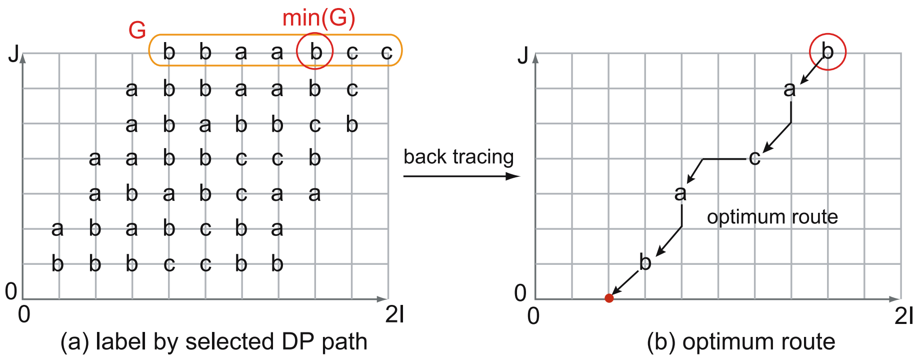


Fig. 8. Back tracing

4 Experimental Results

The performance of their proposed method was computed in simulation as well as real experiments with regard to robustness and accuracy in varying light conditions.

4.1 Experimental Results of Orientation Estimation

Results in simulation experiments. To determine the accuracy of the orientation estimation, the estimated angle using the proposed method is compared to ground truth. Table 1 shows the results in simulation experiments evaluating 360 patterns (1 degree each). In comparison to the performance of general methods based on the least-squares method [3] and the second-moment method [4] using "white bar" ID plate, our method has better accuracy in orientation estimation.

The accurate center position of the blue/yellow colored circle for main marker can not be obtained, when the circle's perimeter has noise. In this case, we evaluate the robustness of our method using the pattern in which the center position of the circle translate to its neighbors. The noise 1 in Table 1 is an area of 3x3 pixels except for the center. The noise 2 is an area of 5x5 pixels except for the center and the noise 1. Five pixels represent 25 millimeters. The SSD in Table 1 means linear matching using the sum of squared difference to estimate the orientation. The SSD is better than proposed method when a very accurate center position (noise 0) is obtained. However, our method is effective with respect to errors in the center position of the circle because the DP warping function can obtain the optimum correspondence against the gap.

Results in real experiments. Table 2 shows results in experiments using the real vision system, in which a camera is mounted at a height of 4,000 mm. We can see that our method has almost the same performance as the general method, and it works well with respect to the "white bar". This shows that our method can obtain the direction of opponent robot's front, and this information is useful to intercept the passing ball.

Table 1. Average of absolute errors of orientation estimation in simulation experiments [degree]

	proposed method		general method	
noise	SSD	DP	least-squares method	second-moment
0	0.30	0.76	0.85	1.08
1	1.71	1.10	-	-
2	4.20	1.75	-	-

Table 2. Average of absolute errors of orientation estimation in real experiments [degree]

	proposed method	least-squares method	second-moment
white bar	0.85	1.17	0.96
patch pattern	0.95	-	-

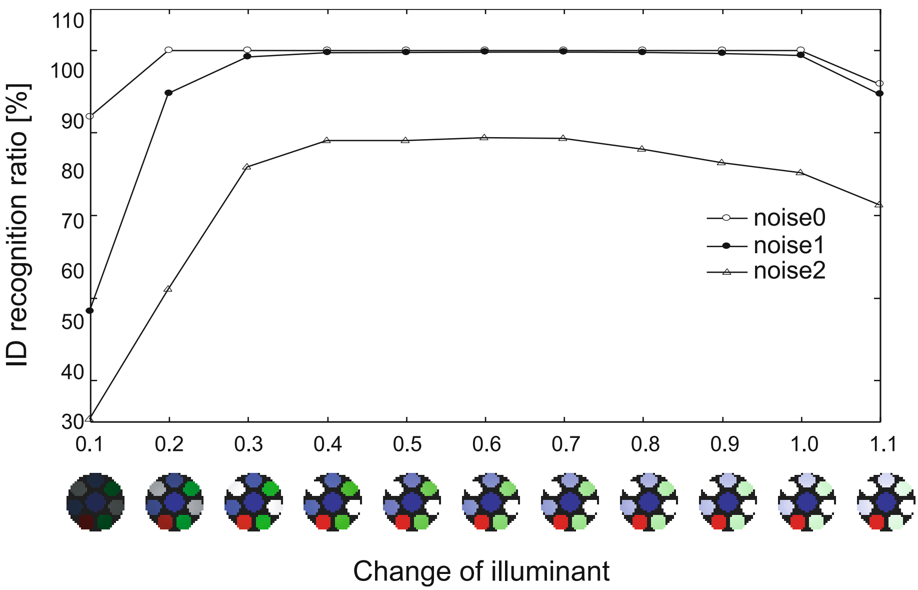


Fig. 9. Result of ID recognition in simulation experiments

4.2 Experimental Results of Object Identity

Results in simulation experiments. To determine the robustness with respect to varying the light condition. A model of illuminant and the marker are created by CG, the pixel intensity of the input image is created by changing the illuminant. Figure 9 shows ID patterns under illuminant changes in the simulation and identification performance against the 11 unique robots. Our system is performance is stable against the change in lighting conditions. However, the recognition ratio decreases at the noise 2. When the error of the center is two

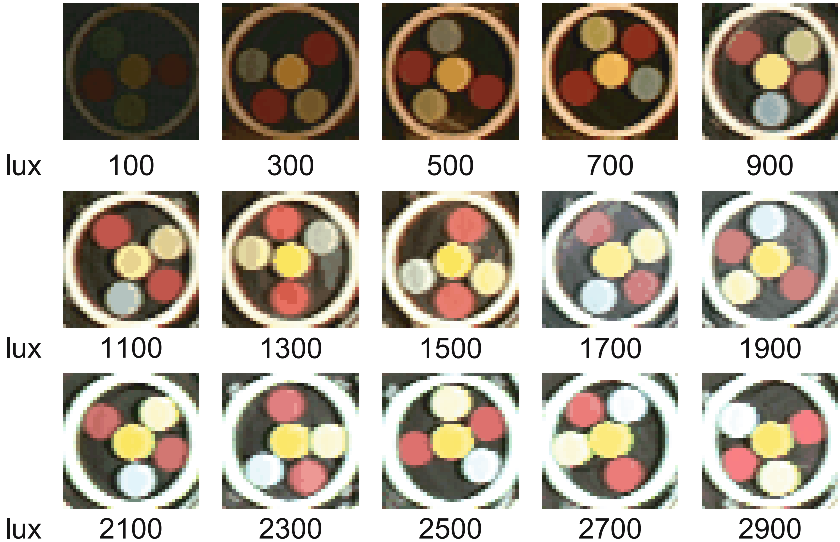


Fig. 10. Images captured under the illuminance of ranging from 100 to 2,900 lux

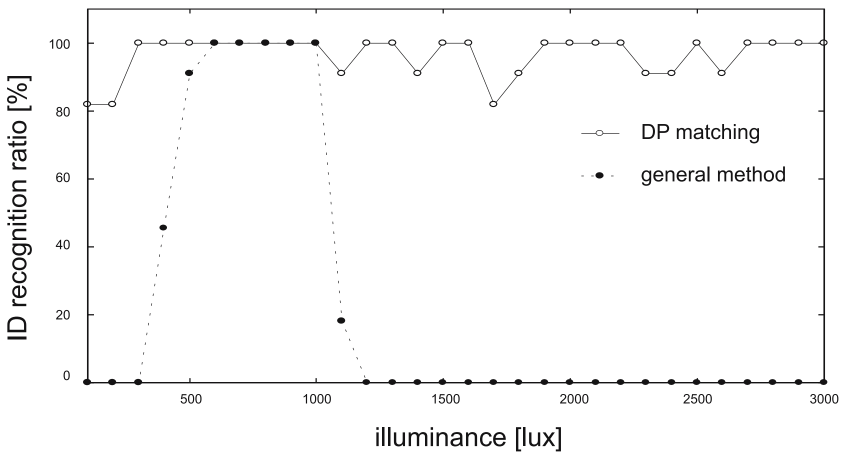


Fig. 11. Result of ID recognition in real experiments

pixels, the center is near the edge of the main marker. Therefore, it is difficult to calculate the 1-dimensional signal, and the recognition ratio decreases.

Results in real experiments. Figure 10 shows images captured under the illuminance ranging from 100-to-2,900 lux. In the experiment, we evaluate 330 images for 11 unique IDs with varing light condition(100$\sim$3,000 lux). Figure 11 shows object identification ratios for 330 images. Note that the general method means color segmentation based object identification adjusting the threshold to obtain high performance for lighting condition between 600 to 1,000 lux. On the other hand, for reference patterns of our method, only the images captured under the light of 1,000 lux are registered. It is clear that our method has a better performance with respect to varying light conditions, because our approach is not based on color segmentation rather it is based on matching using changes in intensity obtained by scanning at a constant radius from the center of the robot.

5 Discussion

This section describes some of the benefits of the proposed method.

- **Easy handling for set up**
  In order to register reference patterns for each robot's ID, the orientation is obtained by clicking the front of the robot to assign an ID for each of our robots. There is no need for making rule-based reference table for object identification.
- **Easy to modify the patches**
  Since the white bar is used to estimate the robot's orientation in general method, the area for pasting more patches of sub-markers is restricted. However, our method allows for more space on the top of the robot. Moreover, it is very easy to modify the patch pattern because of its easy set up.
- **Robustness with respect to varying light conditions**
  There is no perfect color segmentation. Even if the lighting conditions are changed by meteorological effects, our method can work well because the changes in intensity are used for detecting a robot's orientation and identity.
- **Obtaining direction of opponent robot**
  Our method for estimating the robot's orientation works well to any shaped-patch patterns such as "white bar". Therefore, it is possible to know the direction of the opponent robot's front. This means our robot can intercept the ball passing between the opponent robots.

The demerit of the proposed method is as follows. Our method is converted to a 1-dimensional signal. Therefore, if the center of circle can't be calculate accurately, it is difficult to convert to it to a 1-dimensional signal accurately. To calculate accurately, the object identity and orientation is necessary to suppress the error of the center position within two pixels. Moreover, in the case of estimating the ID, it is necessary to compare between input pattern and all reference patterns. Therefore, as the number of robots increase the computational cost is increases.

6 Conclusion

This paper describes a novel approach for detecting orientation and identity of robots without color segmentations. We show that the proposed method achieves accurate performance in orientation estimation, in comparison to the general method, as well as its robustness with respect to varying light conditions. The system using the proposed method runs in real time on a Xeon 3.0GHz, PC, as such the system can be completely setup in a short amount of time by a single operator.

Future works will focus on more automation in the registration procedure of reference patterns.

Acknowledgement

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